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An Assessment of Media Consumers' Ability to Distinguish the Level of Post-Processing in Journalistic Images

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An Assessment of Media Consumers' Ability to Distinguish the Level of Post-Processing in Journalistic Images

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Abstract

Photojournalists are held to a high degree of ethics because of the importance and impact of their work. To address this, several professional photojournalist organizations and publishers have created guidelines on how to appropriately post-process an image. Today the average media consumer is exposed to a diverse news landscape, and there is a tendency for consumers to trust photojournalistic images as being representative of the truth (Farid, 2006). This research considers to what extent can the average media consumer distinguish between ethically and unethically post-processed images.

This study aimed to discover how well people can distinguish between three categories of images when viewing them quickly on their mobile devices. Using a web-based survey, participants were asked to identify various images as either *original, enhanced*, or *manipulated*. Original images had post-processing limited to cropping and having the aspect ratio changed. Enhanced images had aesthetic changes and did not attempt or intend to change the content or meaning of the image. Manipulated images either had material added, removed, or significantly changed. Furthermore, the image dataset was annotated to describe broad content characteristics such as people vs. no people and inside vs. outside. A Friedman test with a pairwise comparison with a Bonferroni correction was utilized to determine if there were differences in the percentage correct by semantic categories (People/No People, Indoors/Outdoors) and manipulation sub-categories (Add, Remove, Change).

Recruited through social media and word of mouth, 1,919 participants responded to an average of 101 images out of a total of a possible 164, with an average of 1,180 responses per image. Participants were encouraged to provide their first impression. Responses were more likely to label the images as original (53.9%) compared to identifying them as enhanced (30.1%) or manipulated (16.0%). On average, only 36% of the images were correctly identified. Overall, participants' responses indicated that unless the manipulation was overly apparent or semantically absurd, they believed that the image must be either the original or enhanced.

Chapter 1

Introduction

Having access to objective news sources is integral for shaping a world view based on reality (Mothes, 2017). This is not a new idea. The news is considered by many to be the fourth branch of the democratic system after the judiciary, legislative, and executive branches (Cater, 1959). It is what keeps the general public (the voters) informed. Americans are very concerned about the quality of the news they see on social media. However, twenty-eight percent currently get their news from social media according to a Pew Research Poll taken in July 2019 (Perrin & Anderson, 2019). Unfortunately, factual, unbiased reporting could be difficult to discern within the onslaught of media that is pressured to be compelling. The percentage of Americans looking to social media for their news has increased in the past several years:

> About three-in-ten Americans now get news on social media often (28%), up from 20% in 2018. More than half of U.S. adults get news from social media often or sometimes (55%), up from 47% in 2018. About two-in-ten (18%) say they hardly ever get news from social media, and 27% never get news from social media. (Grieco & Shearer, 2019, p. 7)

Most news is viewed alongside other digital media. Media produced for satire, entertainment, or advertisements are often shown alongside the news. The *2019 Internet Trends Report* found that U.S. adults spent 6.3 hours with digital media and 3.6 hours on their mobile devices daily (Meeker, 2019). Though the study did not break down how that time was spent, it illustrates a marked increase from what the same study found a year earlier. In 2018, the average adult internet user spent 5.9 hours, with digital media a day with 3.3 of those hours on their mobile device (Meeker, 2019). With long hours spent with digital media, the headlines and news snippets may become just a part of the background, not leading to any critical thought and thus is inherently trusted.

In research that specifically addresses image manipulation detection, Nightingale, Wade, and Watson (2017) note that there was no one particular factor that leads to participants being able to identify manipulation in a photograph of a common scene. Still, an increase in skepticism had the biggest impact (Nightingale, Wade, & Watson, 2017). Media literacy researchers often suggest a healthy dose of skepticism when receiving new information, despite the source publishing it (Parks & Douglas, 2019). Though it would be impossible to personally fact check every news snippet that appears on a personal social media feed, crucial decision-making news and photojournalism should prompt a deeper dive into the underlying circumstances and the overarching facts of the situation.

Social media sites, like Facebook, are responding to criticism over the 2016 fake news firestorm surrounding the American presidential elections (Ingram, 2019). Facebook began to employ third-party fact-checkers who could label posts with nine different ratings, including True, False, Mixture, Satire, and Opinion (Facebook, 2019). The aim of social media sites is to implement a labeling system or protocol medium to decrease confusion when coming across stories on their platform.

The digital news landscape includes a wide variety of sources (Mitchell, Gottfried, Shearer, & Lu, 2017). The Pew Research Center studied the relationship between different levels of trust in the news, and they found that it correlated to political party affiliation, political engagement, and people's overall willingness to trust others when surveying Americans (Gottfried et al., 2019). The report outlines that 40% of those who strongly approve of President Trump believe journalists have low ethical standards, which is double others who are or lean Republican, and ten times more than those who identify as or lean Democrat (Gottfried et al., 2019, p. 7). People on opposite sides of the political spectrum who had opposing views of the president had a similar level of loyalty to their news sources of choice (41% of strongly approving Republicans and 44% of strongly disapproving Democrats) (Gottfried et al., 2019, p. 18) The lack of trust in the news source does not always translate into a skeptical view of photojournalism, which is explored in the next section.

Photojournalism and Image Manipulation

Photographs as an accompaniment to a news article often have powerful iconographic effects, cementing themselves in our public consciousness as the embodiment of an event or time (Dahmen, Mielczarek, & Morrison, 2019). Images can be deceptive, even if not manipulated in post-processing efforts, and not deceptive, even if manipulated (Bátori, 2018). Putting these two statements together illustrates the ethical quandary that belies photojournalism. Journalistic images used for documentary news media need to represent the facts accurately. Successful news images are often compelling to look at and can become icons that represent the event or a series of events. News can be placed alongside other digital media where there may be ads, personal stories, opinion pieces, satire, and completely deceitful information. It is important that the consumer can distinguish between images that are journalistic, deceitful, and illustrative. Shen, Kasra, Pan, Bassett, Malloch, and O'Brien (2019) discuss how the harm of manipulated imagery extends to distorting the viewer's memory, impacting decision-making, and increasing the credibility of the fake. Understanding how well people can discern between accurate depictions and manipulations is paramount in understanding how to protect them from this potential harm.

In 1990 a *New York Times* opinion writer wrote a bleak forecast concerning the credibility of photojournalistic images:

> In the future, readers of newspapers and magazines will probably view news pictures more as illustrations than as reportage, since they will be well aware that they can no longer distinguish between a genuine image and one that has been manipulated. Even if news photographers and editors resist the temptations of electronic manipulation, as they are likely to do, the credibility of all reproduced images will be diminished by a climate of reduced expectations. In short, photographs will not seem as real as they once did. (Grundberg, paragraph 3)

Many images in modern publications are retouched, manipulated, or perfectly curated, but with a photojournalistic image, people tend to trust them. Viewers tend to trust the authenticity of a photojournalistic image, particularly if the image is published from known and trusted sources (Norris, 2017). Hadland, Campbell, and Lambert's survey (2015) of the global photojournalism community found that image manipulation was a pressing issue for photojournalists, with 76% regarding it as a serious problem. However, 25% of respondents in the same study reported to regularly manipulate their images, at least occasionally, against photojournalistic standards (Hadland et al., 2015).

Though the photojournalistic image is not entirely untrusted, as Grundberg (1990) forecasted, there is cause for concern over image credibility.

Trust in News Photography and Sources

Trust in news information sources varies, and within different categories, there are sources with different persuasive intents. Though there is some skepticism in available news sources and their published content, consumers take the information presented at face value when they trust the source (Newman, Fletcher, Kalogeropoulos, Levy, & Nielsen, 2018). A reputable news source should adhere to strict and publicly posted photojournalistic ethics, community-sourced photos, and news sources that aim to persuade their viewers. Trusting images published through these news sources often comes with trusting the source itself (Norris, 2017). The source of information is often the means for verifying the credibility of the published media, but frequently it does not tell the whole story.

Statement of the Problem

As many factors are layered in the decision to trust any news story, it is difficult for the average observer to know what to trust and what to discard as biased or untrue media. Norris from the University of Alabama demonstrated in his thesis that the credibility of the image relies heavily on the information source. Modern media consumers rely more on the source's reputation than the image itself when making decisions about the truthfulness of the subject matter (Norris, 2017). Another study by Nightingale, Wade, and Watson (2017) reported that when participants were prompted to be skeptical of the images, they were more likely to notice the manipulations correctly than without the added prompt. Otherwise unbelievable news stories are passed around and trusted by the general public when others who share their world view also share the news (Mihailidis & Viotty, 2017). With many factors layered in the decision to trust any singular news story, it is difficult for the average observer to know what to trust and what to discard as biased or untrue media.

With an increasing number of images being uploaded and shared online, the ability for the average consumer to accurately distinguish between photojournalistic images that are real or manipulated can be difficult. Little is known of the extent to which the general public can determine on first impression the level that images are processed. Asking participants to distinguish images that have been manipulated (processed unethically), enhanced (processed ethically), or unaltered is a next step in understanding how media consumers interpret the image content published by news sources.

Chapter 2
Theoretical Basis

The ability of the average media consumer to discern the amount of post-processing in a photojournalistic image is a part of a more comprehensive body of work about media literacy. Media literacy covers a broad realm of research, most of which are outside the scope of this thesis. The current study focuses on a subset of media literacy, namely visual competency. The images within the data set must be created by the current governing rules of the photojournalistic community to test the visual competency of the general media consumer. This chapter also discusses the ethics of creating and publishing photojournalistic images.

Visual Competency

Media literacy is a term that encompasses the ability of the viewer to comprehend the lexical, visual, or audible information published (Griffin, 2008). Griffin goes on to describe the relationship between visual competence and media literacy. He explains that visual competency lies within media literacy as the ability to understand both the composition of the image and the symbolic nature of the work itself. Griffin places the importance of understanding media as a crucial ability necessary to interact with the media. Griffin writes:

> Human relationships with technology, the critical analysis of information, and the role of journalism in society all remain major topics of concern for media literacy educators, whose interest in patterns of media use and interpretation is closely tied to an interest in democratic participation, civic life and the notion that democracy depends upon a critically informed citizenry. (Griffin, 2008, p. 116)

To understand the image in both context and content, the media consumer must understand how the source of the image operates. For example, it is possible that media consumers from a country where the government strictly controls the press may or may not trust those images more than an image that was sourced directly from a citizen journalist or foreign correspondent. The visual competency of the average media consumer is an essential factor in creating ethical guidelines for photojournalism. Being able to understand what is being presented in the media on both a compositional and on an inferential level leads to a higher understanding of the published work.

Overview of Digital Image Creation

Photographs go through processing steps where decisions are made at each step that impact what the image looks like in the end. These individualizing steps are inevitable in creating a photo. Currently, many photographers are pioneering different methods that change the photograph, before ever bringing it into post-processing (i.e., Photoshop). Ease of access to high-quality photographic equipment democratizes this process allowing for rapid experimentation and leading to more creative processes. A digital image is formed by light being focused through a lens system onto a sensor, controlled by a shutter, with the light then converted into electrical signals that are processed by an onboard computer chip and then saved. This process can take many forms. A comprehensive discussion of camera mechanics can be found in *Basic Photographic Materials and Processes* (Stroebel & Zakia, 2009) and *The Manual of Photography* (Allen et al., 2011). Because of the physical and optical properties of the photographic process, this study draws the line on what constitutes a manipulation based on processes that occur after the image has been recorded onto a digital storage device directly from the camera.

Photojournalism Ethics for Photo Manipulation

Photojournalism ethics for photo manipulation vary amongst sources regarding the technicalities of what is and is not allowed. However, there is a consensus on the issue of protecting the integrity of the image by limiting what manipulations can take place. This section outlines the perspective of image authenticity standards for the recent historical and modern perspectives on image authenticity as it pertains to image manipulations in photojournalism. The term "fake news" has had a resurgence in the popular vernacular. The term was coined in the 19th century and predated by the term "false news" (Merriam-Webster, 2017). Devine recounts, there has been a litany of examples from the past several decades, not even including twenty-first century examples (1996).

There are scores of examples of digitally manipulated photographs published as a portrayal of reality. Popular examples have been compiled in Devine's thesis, which include:

- *Vancouver Province* puts Alexander Mogilny's head on Pavel Bure's body to create a photograph of Mogilny in a Canuck's uniform (August, 1995);
- *Vancouver Sun* creates a photograph of a Vancouver player skating and holding the Stanley Cup over his head to simulate the Vancouver Canucks

celebrating winning the Stanley Cup (June, 1994) (Chris Campbell, 1995, p. 3);

- *Time*'s cover photograph of O. J. Simpson's arrest (June 21, 1994) is digitally manipulated so that his facial shadows make him appear more sinister;
- *National Geographic* (February, 1982) published a manipulated cover photograph where the pyramids at Giza are moved closer together to make a vertical photograph rather than a horizontal one;
- Production personnel at the *Orange County Register* mistakenly "corrected" the colour of a swimming pool dyed red by vandals back to blue (Becker, 1991, p. 388);
- *Newsweek* merged two photographs to imply that Tom Cruise and Dustin Hoffman were posing together when they were actually on opposite coasts at the time (Kenney, 1993);
- *TV Guide* placed Oprah Winfrey's head on Ann-Margret's body, darkening Margret's body and slightly lightening Winfrey's head (Kenney, 1993);
- *Texas Monthly* put Anne Richards, Governor of Texas, on a motorcycle by superimposing her head on a model's body (Kenney, 1993);

(Devine, 1996, pp. 2–3)

Clearly, the scope and the abuse of disingenuous portrayals of images for editorial effect dates before the wide-spread use smart phone photography and easy editing and sharing applications of the modern era. Despite this, there seems to be a significant lack of popular resources and education for real-time fact-checking for news images.

Recent historical perspective

Without human intervention, the camera's images were seen as more objective than an artist rendering (Mitchell, 1992). Popular camera companies promoted the image as a direct, realistic capture of the image. Throughout the twentieth century, the sentiment was reinforced by camera companies,

> Kodak's well-known advertising slogan: "You push the button, we do the rest." This slogan epitomizes the mechanical aspect of the process, suggesting that the act of taking a photograph involves nothing more than pushing a button and that no additional intervention is required. (Mitchell, 1992, p. 28)

Traditional photographic processes were seen as an authentic representation of the scene, even though there are well-cited photo-manipulations done with analog processes (Mitchell, 1992). The relative lack of human intervention, coupled with the mechanical process of rendering a scene, created a false sense of trust in the photographs that resulted from analog processes (Gavard, 1999; Mitchell, 1992). At the same time, another group of theorists was pushing back on the objectivity of a photograph. Gavard argued that since manipulation in the form of retouching negatives was created the same year as the daguerreotype was publicized, that people can manipulate the lighting and position of the camera to create the image they want (1999). In 1989, the *Wall Street Journal* cited a statistic from the Rochester Institute of Technology that one in ten color reproductions had been altered in ways that included adding, removing, or moving content in the image (Ansberry, 1989). They then prophesized that with digital images and continual improvement of retouching software, the numbers would only increase.

At the end of the 20th century, forecasts arose that digital images would soon be of comparable quality to film photographs. There were general warning trends of the digital photograph's lack of objectivity in recording reality: "Press photographers scented a cybernetic dystopia in the making – a world infested with subversive, uncontrollable image hackers who would appropriate photographic fragments at will and recombine them into fictions" (Mitchell, 1992, p. 16). During this time, the National Press Photographer Associations (NPPA) and the non-profit Artist Rights Foundation tried and failed to create regulations around publishing edited works (Mitchell, 1992). These organizations failed because, by the time they created the standards, means of editing images and video had become so decentralized that it was impossible to enforce the distribution and publishing of edited media.

Listing the numerous examples of photojournalistic manipulations is beyond the scope of this study. Examples of recent and historical image manipulations in the news are well illustrated in current papers. "Digital doctoring: How to tell the real from the fake" describes examples from war photography and pop culture (Farid, 2006). "Photo-graft: A Critical Analysis of Image Manipulation" discusses an overview of the nineteenth and twentieth-century image manipulations and photo-montages (Gavard, 1999). "Photographs Do Not Always Reflect Reality" names examples of manipulated images from a variety of different genres relating to politics and war while juxtaposing them to paintings (Henry, 2013). *The Reconfigured Eye* compares image manipulations of analog and digital photographs (Mitchell, 1992), "Do Readers Believe What They See? Reader Acceptance of Image Manipulation"(Garrison, 2015) and "Ethical

Considerations for Digital Manipulation of Sports Photography" (Oriez, 2009) enumerate examples of image manipulations found in news sources.

Current standards

The National Press Photographers Association (NPPA) and other news outlets post their ethical image post-processing criteria. The NPPA publishes ten *musts* and seven *shoulds* to follow in ethical photojournalistic image creation (NPPA, n.d.). Permissible post-processing steps are listed as "Editing should maintain the integrity of the photographic images' content and context. Do not manipulate images or add or alter the sound in any way that can mislead viewers or misrepresent subjects." (National Press Photographers Association, n.d., pt. Code of Ethics, bullet 6). Other rules cover how the picture should be taken as not to distort or stage events.

World Press Photo is a research group out of Amsterdam, in the Netherlands, who strives to create high-quality photojournalism through education, outreach, and grants. Canon and the Dutch Postcode Lottery supports the group. World Press Photo sponsored a report, which outlined guidelines of what constitutes a manipulation versus ethical processing (Campbell, 2014). The report found that globally the photojournalists interviewed agreed that the following were the general guidelines to follow for post-processing:

1. Manipulation was seen as involving material changes to an image through the addition or subtraction of content and was always deemed unacceptable for news and documentary pictures.

2. Adjustments (such as limited cropping, dodging, and burning, toning, color adjustment, conversion to grayscale) to photographs were accepted. These changes were usually described in terms similar to those detailed above: “minor” changes, such as those said previously to have been used in darkrooms, were permitted; “excessive” use of such adjustment was not.
3. What constitutes a “minor” versus an “excessive” change is necessarily open to interpretation. Respondents said that judgment was on a case-by-case basis and often used the anachronistic terms of the darkroom analogy. (Campbell, 2014, p. 12)

The report states that most hiring or commissioning of photographers or licensing of photojournalistic images is done mainly by trust and reputation. Sometimes photographers are given a brief on what is considered ethical. Photo editors are often the first line of defense when an image’s authenticity is questioned, but after an initial file inspection, a forensics team must be pulled in. The report stated that at the time of publishing, only the Agence France-Presse (AFP) utilized a forensic software program called Tungstenge (Campbell, 2014).

Associated Press writes in their code of ethics that “AP visuals must always tell the truth. We do not alter or digitally manipulate the content of a photograph in any way” (Associated Press, 2020, para. 1). However, they put in caveats that which they consider appropriate post-processing:

> Only retouching or the use of the cloning tool to eliminate dust on camera sensors and scratches on scanned negatives or scanned prints are acceptable.
>
> Minor adjustments in Photoshop are acceptable. These include cropping, dodging and burning, conversion into grayscale, and normal toning and color adjustments that should be limited to those minimally necessary for clear and accurate reproduction (analogous to the burning and dodging previously used in darkroom processing of images) and that restore the authentic nature of the photograph. (Associated Press, 2020, paras. 1–2)

AP limits the above-accepted manipulations by stating,

> Changes in density, contrast, color and saturation levels that substantially alter the original scene are not acceptable. Backgrounds should not be digitally blurred or eliminated by burning down or by aggressive toning. The removal of "red eye" from photographs is not permissible. (Associated Press, 2020, para. 3)

Despite strict rules for mainstream photojournalists, the vast media landscape includes images sourced using non-traditional means. These images can come from security camera footage or citizen journalists. Citizen journalists may be bystanders at the scene or other types of amateur journalists not associated with the publication.

Conclusion

Understanding the whole visual work and how it was created enables the media consumer to see the intentional decisions made by the photographer or publisher in the framing of an event. Having reputable sources is important in alleviating the amount of technical and background knowledge a viewer requires to determine what a news image means. Chapter 3, the Literature Review, includes a deeper discussion of how individuals and images interact, both within and outside of the context of journalism.

Chapter 3
Literature Review

This literature review presents topics germane to the present research context, including media forensics, photojournalism, and human perception. The media forensics section discusses the limitations of the human visual system in detecting manipulated images. Though there are techniques developed to determine the provenance of an image computationally, these are outside the scope of this study (Rocha, Scheirer, Boult, & Goldenstein, 2011). Two sections in this chapter focus on photojournalism. The first section explores how image post-processing is seen within the photojournalism community. The second section reviews how journalism has the power to persuade the audience's understanding of current events. The final section discusses how the human visual system processes change in vision experiments.

Media Forensics

Media forensics is the field of study that seeks to understand how to determine the provenance of media. Images, audio, and video are assessed for truthfulness to their source (Kraetzer & Dittmann, 2015). Media is tested for limited and large-scale changes from reality. Several researchers have pioneered this area of image manipulation detection (Ehinger et al., 2016; Farid, 2006, 2009; Farid & Bravo, 2008; Mader, Banks, & Farid, 2017; Nightingale et al., 2017; Schetinger, Oliveira, da Silva, & Carvalho, 2017). They have studied the nature of people's ability to discern if an image is manipulated and in what manner it was manipulated. They found that people have difficulty with this task even when the manipulations do not obey the physics-based properties of the real-world scene presented in the image (Ehinger et al., 2016; Farid &

Bravo, 2008; Schetinger, Iuliani, et al., 2017; Schetinger, Oliveira, da Silva, & Carvalho, 2017). An example of an image that would be manipulated against a physical constant would be an image of two trees on a sunny day where their shadows go in opposite directions. Another example would be a picture of three people in front of a mirror where one does not have a matching reflection. Though there *could be* extenuating circumstances for each of these anomalies, they generally do not happen without intervention.

Researchers understand that the human visual system excels at many tasks. It navigates the world better than computer vision algorithms (Farid & Bravo, 2008). Farid, in a paper co-authored with Bravo (2008), found that although the human visual system is well adapted for tasks such as rapid scene recognition and hyperacuity, image manipulation detection is not its forte. Rapid scene recognition is the ability to remember an image or pick it out from others after only seeing it for a short time (Potter, 1976). Hyperacuity is the ability of the human visual system to resolve a stimulus even if it is moving (Westheimer & McKee, 1975).

Image composites are images spliced together to make a new scene. In their creation, physics-based features are often overlooked. These features, such as the shadows or highlights, will interact with the subject in precise ways. Another feature difficult in image composites is a planar relationship, meaning that right angles remain right angles when the image is orthogonally corrected based upon the original markers in the scene. Farid and Bravo (2008) showed participants scenes where shadows were manipulated, and they found that participants were nearly perfect in identifying the manipulation. When the shadows were the opposite of the environmental lighting, the twenty participants identified the manipulation 95.5% of the time. When considering all other cases, participants had a near chance ability to identify if the image had a manipulated shadow (Farid & Bravo, 2008). When viewing images with planar distortions, Farid and Bravo found that observers underestimated the amount of distortion created by skewing objects on otherwise rectilinear features such as text and images on a carton. In their third test, the researchers found that the observers also had deficiencies in detecting falsely rendered reflections. The participants were not able to predict if a reflection of a rendered object in a three-dimensional space was correct, with an average accuracy of 57% in an average response time of 7.6 seconds. The researchers suggest that instead of relying on the human observance of images, simple computational tests be used to detect simple geometric inconsistencies.

In an article in *Significance,* Farid explains simple ways to combat image manipulation that eludes human detection, such as changes in lighting the object (2006). One such way to detect if shadows were created correctly is to create vectors that trace the intensity of the light; the proper shadow placement can then be equated. This method, however, was not recommended for manipulations to the shadow cast on the ground or detecting identical pixel patterns next to each other (Farid, 2006). For these types of manipulations, he recommends relying on looking at the statistical difference between pixels that are images from Color Filter Array (CFA). Through traditional manipulation techniques, these correlations are destroyed and can be detected.

An article published in *Perception* by Mader, Banks, and Farid discusses the ability to identify computer-generated portraits (2017). Though modern computer-generated image (CGI) methods create convincing portraits, observers were able to reliably distinguish between photographic and rendered portraits depending on the resolution of the images. Observers had a bias toward marking images as photographic rather than rendered, but minimal training reduced the bias. Through incentives and training, participants' ability to discern between the two types of portraits became more accurate (Mader et al., 2017). However, the researchers found that when the eyes of the portrait were masked out, the task became significantly more difficult for participants. When the faces presented were familiar to the participants, they were able to detect that the images were photographic rather than computer generated somewhat better than non-familiar faces.

Photojournalism

A sample of newspaper readers in the Highland-Alhambra area of Madison County, Illinois was surveyed regarding their opinions on image manipulation by photojournalists. They reported widely believing that the local news images were more drastically manipulated with methods that they found concerning or possibly deceitful at a higher frequency than they were in reality (Oriez, 2009). Oriez (2009) cites a list of well known, highly publicized manipulation scandals that rocked photojournalism over the last 30 years as well as responses by photojournalist professionals. As a result of their responses, the NPPA publicized strict codes of ethics in the hope that the general public trusts these images to be authentic. Oriez discusses the degree to which the public has accepted the abilities of a well-versed user of Adobe Photoshop. Even in 2009, media consumers knew what the software was capable of, but were unsure of the ethical lines of manipulation in photojournalistic images.

Oriez (2009) asked participants which types of manipulations were the least and most offensive by rating them on a scale of 1 to 5, with five being the most acceptable. He found that spotting (the removal of dust or defects), color, or density corrections were the most accepted. Moving, removing, or adding subject matter such as objects or people were the least accepted. *Cropping* was assigned a 4, *dodging* and *burning* were a 3, and removing distracting elements was a 2. More than 60% of respondents reported they believed that the three most accepted manipulations were carried out daily by photojournalists, while 81% stated that images were cropped. Oriez found that most respondents were undecided about whether dodging and burning were ethical or not. Though, the majority who answered the question chose that the operation was done daily. A third of the respondents answered that they believed that the three least acceptable manipulations were done regularly by photojournalists. The study found that the more these manipulations were carried out, the less trust the respondents had in the publication's images (Oriez, 2009). The three least accepted manipulations were, across the board, considered unethical by photojournalists (Oriez, 2009). The participants' answers to the survey questions demonstrated that these news media consumers had a higher tolerance for image manipulation than the media editors at that newspaper.

Journalism as a Persuasive Force

Through the years of visual reportage, the photojournalism industry has legitimized itself as a credible source of news (Newton, 2001). Different sources of news have different agendas. With different means of publishing and framing the news, these groups can send different messages to the general consumer. Newton (2001) identifies four different groups—public, government, press, and economic interests—that have each developed visual codes and socially constructed images to present news in their unique style. Visual reportage, more specifically photojournalism, is highly persuasive. Newton describes the persuasive force as:

> Visual reportage legitimizes ways of looking at other people and ways of looking at ourselves. It enters the public consciousness under the guise of authority of the press: This is True. This is what happened. This is what the situation looked like. This is what the people looked like. The context has been one of *assumed truth.* (Newton, 2001, p. 89)

However, the framing of the image and the consumer's knowledge of the event will change how the image is received and understood. Griffin (2008) brought up the example of the headline 'Toppled' on the front-page section of the *Minneapolis Star Tribune*; 10 April 2003 was paired with an image of an American soldier looking at the statue of Saddam Hussein in Iraq's Fadus Square. What this picture did not show was the mostly empty square and the very deliberate photo-op moment created by the Americans to bring the statue down. The photograph framed the destruction of the regime's icon as an Iraqi lead celebratory and spontaneous moment (Griffin, 2008). Without seeing other images from the event, it was easy for the press to create its narrative of the event without manipulating any pixels.

The news can also be used to spread sensational media. When enough coverage is given to a particular event, it is seen as being more legitimate (Mihailidis & Viotty, 2017). Coverage of a particular event or story is characterized as enough coverage to cause a legitimization when it is not just covered by social media or blogs but covered by mainstream news networks in depth. Mihailidas and Viotty (2017) explain media spectacles as, "Spectacles in the mass media space produce events that can be constructed, altered, and shifted for purposes of maintaining, reifying, or destabilizing spectacles" (p. 442). Crowdsourced information or citizen-led networks can also create and perpetuate misinformation (Mihailidis & Viotty, 2017). Thus, it can become difficult for the average consumer to sift through different sources for the truth of the story. This could be especially true when there are two sides of the story, and those sides have polarizing world views.

Human Visual System Perception of Images

In order to see a change, a viewer must have a memory of the before state (Beck, Levin, & Angelone, 2007). Beck et al. (2007) go on to explain that change detection is even easier if the viewer expects the change. People who participate in change blindness studies often expect to detect more changes than they can identify. The inability to identify what changes are being missed is called *change blindness blindness* (Beck et al., 2007). Change blindness blindness can lead to the overconfidence of viewers to trust their memory when viewing images of natural scenes as people often glance over the scene for semantic understanding and retain the gist of the image (Ball, Elzemann, & Busch, 2014). The phrase “look but fail to see” is frequently cited in change blindness research. Change blindness can be caused by distractions or the change happening between saccades or blinking (Ball et al., 2014).

Ball et al. (2014) created a data set of 34 real-world scenes and manipulated each of them in 20 ways using a free image editing software, GNU Image Manipulation Program (GIMP) (Ball et al., 2014; “GNU Image Manipulation Program,” 2018). They manipulated the images in ways that changed the position or color of subjects in the scene or deleted them altogether. The researchers had 10 participants view each scene and note the first three manipulations they would expect to see in that image. They found that the participants expected to see the same manipulations that the experimenters had created. The image (A) and its manipulated pair (A’) were then shown to the participant in quick succession following an A, A’, A’, A, A pattern that has blank screens in between. The participant had to indicate when they saw the change. Out of all correct responses, Ball et al. reported that it took 8-14 presentations of the images for participants to find the change. Position changes took an average of eight presentations to identify the difference. Deletions took an average of 12.31 presentations, and color changes took 13.91 presentations to identify correctly. When the participant expected to find the change, fewer presentations were necessary. Changes to the image that covered a substantial area of the image also required fewer presentations for a correct finding. The researchers suggested that, in the future, when creating a data set, the changes should be on parts of the image that were not as obvious to possibly obtain different responses from the participants (Ball et al., 2014).

Shadows in an image can give many clues to how objects interact with their background in a real-world scene (Ehinger et al., 2016). When objects in an image are removed, but their shadow remains, the change in the image is detected more quickly than when an object is there, but the shadow is removed or altered (Ehinger et al., 2016). During their experiment, Ehinger et al. (2016) showed participants images through Amazon's Mechanical Turk (Amazon, 2017) that had shadow manipulations as well as filler images. Mechanical Turk is a service that allows researchers to pay people a small amount of money for each task they do. It is often used for soliciting people's time to complete mundane tasks like labeling images, identifying features, or translating words on a large scale. They altered shadows by rotating them, changing their placement or surface texture, and removing them or the casting objects. The researchers found that the participants were not able to detect changes to shadows as well as they could detect changes to objects or surfaces. Ehinger et al. theorized that the participants' poor ability to see the manipulations is because shadows are not as salient as objects in a natural scene.

To understand more about how the average observer views natural scenes possibly requires that they are shown computer-generated scenes and natural scenes. Subsequently, the difference between the reactions is measured. When creating computer-generated scenes for visual or photo-realism, imagers strive to create an image indistinguishable from natural scenes (Elhelw, Nicolaou, Chung, Yang, & Atkins, 2008).

However, when it comes to portraiture, with the right incentives, observers can distinguish between computer-generated portraits and photographic ones remarkably well (Mader et al., 2017).

Conclusion

Understanding which manipulations are more easily detected by the human observer continues to be a valid research topic. Diverse image content and diverse cognitive processes create challenges for researchers. The broad scope of variables makes it difficult for researchers to understand how image manipulation is understood by the average observer. The impact of image manipulation could be better understood through media forensics, understanding the photojournalism industry, and recognizing how people see images. As discussed in this literature review (a) media forensics uses computational and technical understanding to determine if any post-processing has been done to an image, (b) photojournalists create the images and have created ethical guidelines to protect the validity of their images' newsworthiness, and (c) the average media consumer is affected by what they see in the news. Therefore, understanding how the average media consumer understands the images they see is essential in comprehending the magnitude of the impact of image manipulation.

Chapter 4

Research Objectives

Examples of altered photographs in the news and photography's important role in shaping public opinion have been well documented (Choi, 2012; Devine, 1996; Farid, 2006; Henry, 2013; Lester, 1989; W. J. Mitchell, 1992; Müller, Kappas, & Olk, 2012). There have also been studies concerning how the human visual system perceives images and the truthfulness of the contents in real-world or simulated scenes (Ehinger et al., 2016; Farid, 2006; Nightingale et al., 2017). However, there is a lack of research investigating how well people can differentiate manipulated photojournalistic images from originals.

By understanding how media consumers differentiate the authenticity of images, news sources, and social media sites there is an opportunity to better understand how to label and distribute images for the most clarity and upholding the highest ethical standards.

Research Questions

This thesis aims to answer the following questions:

1. Can general media consumers distinguish if a photojournalistic image is an original image or has been enhanced or manipulated?
2. Does the type of image processing or the image subject change the ability of the participant to distinguish between the different levels of post-processing? The different types of processing are:

Manipulation Categories

- Original
- Enhanced
- Manipulated
    - Add
    - Remove
    - Change

Semantic Categories

- People, Indoors
- People, Outdoors
- No People, Indoors
- No People Outdoors

Chapter 5
Methodology

This research aimed to survey media consumers to determine how accurately and quickly they can identify the authenticity of photojournalistic images. Different types of media consumers were reached by using a variety of methods to recruit participants. By using their scores together, anonymously, a picture of the response of an average media consumer was formed. Participants were asked to determine the correct category of processing applied to different images. Image categories were limited to original, enhanced, or manipulated. The survey included 164 images and allowed each participant to respond up to the full set of images. Images were available to participants via a web app, which allowed them to view and respond to each image on their own devices. The participants' response to each image was recorded for analysis.

Images, for the survey, were sourced from local photographers and public domain repositories. Some images were given additional post-processing while others were left as is. Most of the images were cropped to fit the survey mechanism's mobile-friendly format of either square or portrait aspect ratios. A survey mechanism was created to display the images via a web browser. The participants categorized the images into three categories—enhanced, original, and manipulated. Participants were recruited through social media, email, and distribution of business cards. The business cards were distributed in coffee shops, bars, libraries, the New York State Fair, grocery stores and gas stations. Statistical analyses were then completed to answer the research questions.

Post-Processing Definitions

This study describes image post-processing as three categories: untouched, enhanced, and manipulated. Image manipulation encompasses any post-processing that adds or removes subject matter or combines images that change the semantic meaning of the image. A manipulated image is one where the post-processing steps exceed what is accepted to be ethical. Ethical post-processing intends not to change the semantic meaning of the photograph but compensate for technical failure in the imaging pipeline (Hadland et al., 2015). In this study, ethical post-processing will be differentiated by the term *enhanced.* Enhancement of an image includes any processing done to a photograph past the point of capture that is not intended to change the semantic meaning of the image. With an enhancement, post-processing is applied for purposes of adjusting for technology limitations, layout, or minor aesthetic changes (Schetinger, Iuliani, et al., 2017). Enhancements included in this study were derived from Associated Press (AP) Code of Ethics (Associated Press, 2020). Manipulations are defined by post-processing steps that went beyond what is permissible by AP. These manipulations are often found to be past the point of correcting for camera flaws (Hadland et al., 2015).

Creation of Data Set

The dataset includes 164 photojournalistic style images with a variety of image content that was either in its original state, enhanced, or manipulated.

Image sources

Images were collected from multiple sources. Nine photographers and six public domain sources contributed to the dataset of 164 images. Original photographs and supplemental stock images were used to create the manipulated and enhanced image set for this study. An open call to photographers resulted in nine photographers submitting images for use. Photographers retained the rights to their images. The photographers were asked to deliver original "untouched" files. Image files in their native camera raw formats were preferred, but original JPEG files were accepted. Each photographer provided consent allowing the image to be included in the data set and be post-processed for use in this study. Some images were curated from public domain image websites. Images were curated by the researcher to balance image content, not image source.

Image content

To be included in the study, each image was assessed by the researcher and her advisers to ensure it met technical qualifications (correct color balance, in focus, correct exposure) consistent with professional publishing. Images were also selected for their content. Content criteria for the images were:

1. Photojournalistic style,
2. Composition and content that were easily viewed on a cell phone screen,
3. A portrait orientation was preferred over landscape.

The qualifying images were sorted between four content categories: (a) people: indoors, (b) people: outdoors, (c) no people: indoors, and (d) no people: outdoors. Based on the image submissions, *no people indoors* had the fewest number of images included and *people outdoors* had the greatest number of images.

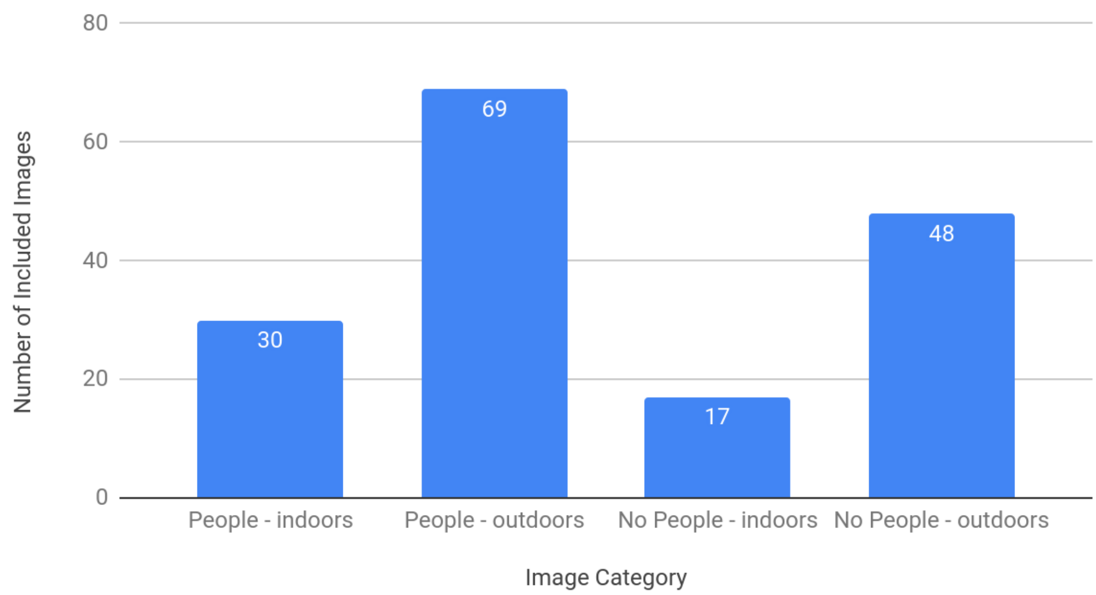


Figure 1. Images are broken down into two main categories (people/no people) and two sub-categories (indoors/outdoors) based on content.

Each image was then post-processed, as explained in the next section.

Post-processing

Some original images were post-processed by the researcher to create the necessary enhanced and manipulated image files in each content category. Some original images were cropped to maintain a uniform appearance of either square or portrait aspect ratios. This was to ensure ease of viewing the images in the survey when displayed on mobile devices. Enhancements altered the image but without intent to change the semantic meaning (Hadland et al., 2015). All enhancements aimed to increase the aesthetic appeal of the images.

Figure 2 provides an example of an enhanced image (on the left) compared to its original (on the right).

Figure 2. The left image is the enhanced version of the image on the right. The image has been cropped, the color balance has been shifted so that the whites appeared neutral (less red), and the image has been sharpened. Original photo: Nesson, Audi, [photograph]. Retrieved February 2, 2019 from Unsplash: https://unsplash.com/photos/u1CAj5HJzO4

The manipulations semantically altered the image. Manipulations were categorized into either additions, removals, or changes. Figure 3 shows the distribution of the image set into these three post-processing categories. There were a greater number of manipulated images to allow for a range of alterations to be represented. Manipulated images were divided into three sub-categories: add, remove, and change. There were 25 *add* manipulations, 17 *remove* manipulations, and 17 *change* manipulations.

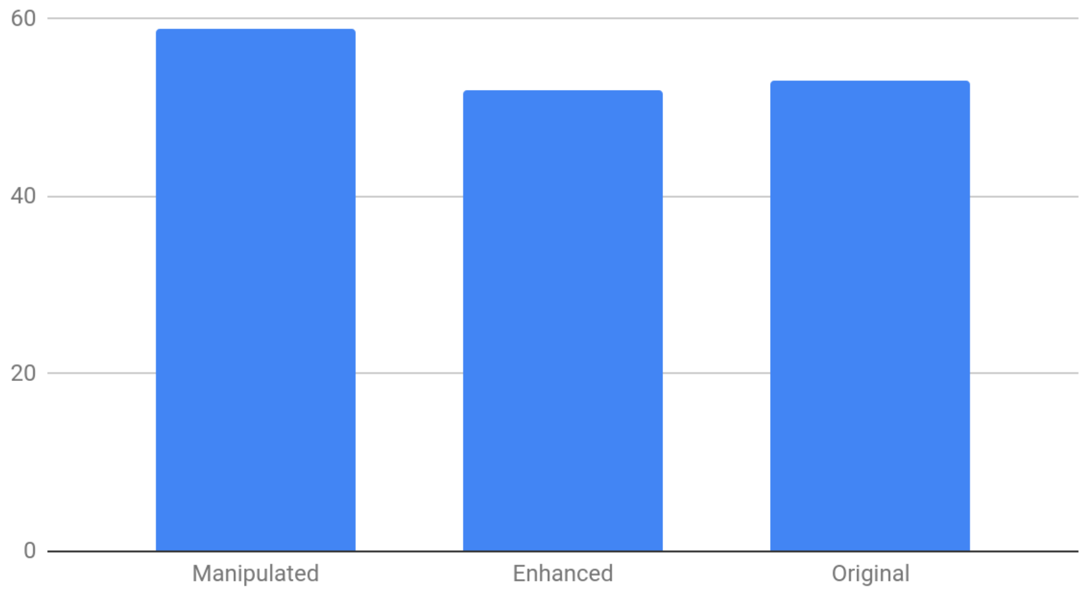


Figure 3. The image set included 164 images. 53 Originals, 52 Enhanced, and 59 Manipulated Images.

Manipulations were done in Adobe Photoshop and Adobe Lightroom. Manipulations altered either the main content or large parts of the image's background. The image examples in Figure 4 were altered in various manners. The left image shows a street in Italy with the removal of the top section of the center building. The middle image shows a couple in the foreground added to a group of collegiate ballroom dancers. The right image shows a dining area, where the ceiling was originally red but was changed to green.

Figure 4. Three examples of manipulated images. The manipulations include a removal (the top of the tower has been removed), an addition (the couple in the foreground has been added), and a change (the ceiling has been changed from red to green). Left: Heusner, Christine. [photograph] (copyright permission of Christine Heusner); Center: Shriver, Emily. [photograph]; Right: Heusner, Christine. [photograph] (copyright permission of Christine Heusner)

There were different numbers of images in each semantic category and manipulation category. A tabulation of the numbers is presented in Table 1.

Table 1

Number of Images in Each Semantic and Manipulation Category

	No People Outdoors	*People Outdoors*	*No People Indoors*	*People Indoors*
Enhanced	12	23	4	13
Manipulated	19	22	7	11
Original	17	24	6	6

Survey Mechanism

The survey was accessible via both computers and mobile devices. The survey began with an introductory statement of the research, followed by the option to participate in the study on the next page. This landing page included a link to the research website, which contained the research questions, further description of the research, sources related to the research, and contact information for the researcher. Images were cached in groups of ten and accessed one-by-one from the database of 164 images. The image with the fewest number of responses was called up as the next image in the series after each recorded response. This allowed the respondent to exit the survey at any time without viewing all 164 images and for all images to have an equal number of responses.

Images were displayed in either portrait or square aspect ratios. The survey mechanism recorded each image's unique identification number, assigned by the researcher, and the respondent's decision about the image's processing category—original, enhanced, or manipulated. The survey was designed so that respondents could not easily download the images.

Participants were asked to determine if the image shown was manipulated, enhanced, or original by either swiping left, right, or up or tapping the buttons labeled M, O, and E on the screen. An example of the user interface is illustrated in Figure 4.

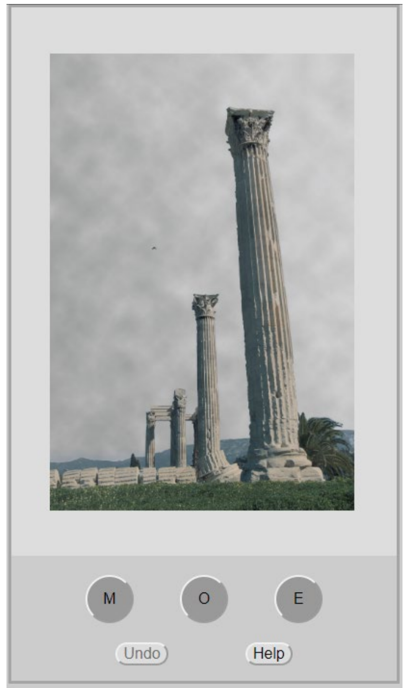


Figure 4. Example of an image displayed in the user interface for the survey mechanism. (Original image: Heusner, Christine. [photograph] (copyright permission of Christine Heusner) Manipulation: blue sky changed to grey clouds)

Participants could quit at any time by leaving the website. All responses were considered in the final analysis. It took an average of nine minutes (excluding outliers) and 16 minutes (including outliers) for participants to submit an answer for all 164 images. More information about time participants spent on the survey is located in Appendix A: Augmenting Information, Table A1. Participants were discouraged from taking the survey multiple times by both the length of the survey and the absence of feedback on their responses that would confirm their accuracy. Users who viewed all the images saw a thank-you notation as well as the end page of the survey when returning to the survey website.

Participant Recruitment

Participants were recruited through social media, targeting no specific group of media consumers. Paid Facebook, Twitter, and Google Ad campaigns were used to recruit a larger pool of participants outside of the researcher's social media connections. Posts on the researcher's social media accounts were used to augment the paid campaigns and included Facebook, Snapchat, Reddit, and LinkedIn. Indirect avenues of recruitment included:

- Distribution of business cards
- Article in a local newspaper
- Blog post on media literacy research and advocacy website
- Word of mouth
- Email recruitment

No demographic information about the user was collected directly, but Google Analytics was employed to collect general location information. Participants were identified by a series of numbers and letters (hash) derived from their device internet protocol (IP) address.

The survey ran from May 8th through October 1st, 2019. Over that time, according to Google Analytics, 3,139 people clicked on the link to the survey. There were 1,919 participants. This can be considered a 61% response rate.

Analysis of Survey Responses

The first research question asked to what extent can general media consumers distinguish if a photojournalistic image has been enhanced or manipulated. For each image, the number of times the image was categorized as original, enhanced, and manipulated was counted. The number of correct and incorrect answers was recorded. For each image, the most popular answer was determined for that image, even when that was not the correct answer. The answers for each participant were analyzed for differences in the number of correct answers as that person progressed through the survey to see if there was a learning curve and to determine if user fatigue was a factor. If a pattern of significant user fatigue appeared as evidenced by a drop off in correct answers after a certain number of decisions, then a comparison of the correct rate before and after that number of views was recorded.

The second research question asked about how different parameters affected the ability of a participant to distinguish between the different categories. Since the data collected had three or more related categories in that the participants had the opportunity to see images of each manipulation category and sub-category, a non-parametric statistical approach was used in the form of the Friedman test. A pairwise comparison was used to test the significance of the results of the test. A Bonferroni correction was utilized for a post hoc analysis. The results and analysis are reviewed in the subsequent chapter addressing how the participant responses answer the research questions.

Chapter 6
Results and Analysis

This chapter reviews the results of the survey, as it pertains to the research questions as well as a brief overview of participant behavior. The participant response data supported the first research question: Can general media consumers distinguish if a photojournalistic image is an original image or has been enhanced or manipulated? When combined with image annotation, participant response data supported discussion of the second research question: Does the type of image processing or the image subject change the ability of the participant to distinguish between the different levels of post-processing?

A further discussion of information from the survey's Google Analytics is included in Appendix A: Augmenting information. The appendix discusses how the participants were directed to find the survey, how long the participant took to respond to each image, how many images each participant responded to, as well as how many times the participant used the undo function to change their previous response to an image.

Participant Behavior

Participants were told to respond to as many images as they wished. There were 164 images in the dataset, but the 328-image maximum occurred as an early issue with the survey mechanism. The 25th percentile represented 39 responses. The lowest response rate was one, and the median was 115 image responses. The 75th percentile was 164 image responses. The distribution of responses was then limited only to participants who saw the corrected survey, with total possible images being 164. The median response was

113 images, and the mean was 99 image responses. The 75th percentile mark was at 164 images. The 25th percentile was 38 image responses. The minimum answer was one image response.

The undo button on the user-interface allowed for participants to change their answer for the last image to which they gave a response. There were 193,827 individual answers, 1,839 responses used the undo feature, which accounted for 0.95% of responses. Only 43 responses used the undo button more than once, and only one response used it a maximum of three times.

Research Question 1

Research Question 1 addressed how well the participants could correctly respond to the images as either original, enhanced, or manipulated. A response was considered correct when the participant response matched the post-processing category of the image.

Participants were more likely to respond to images by selecting *Original* than *Enhanced* or *Manipulated*. Figure 5 shows the number of responses that fall into each image processing category.

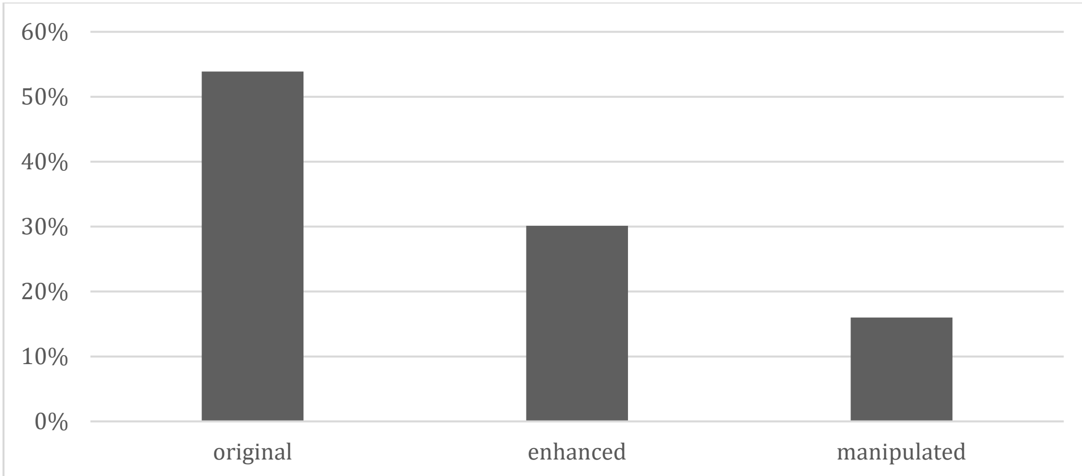


Figure 5. Original was the response 104,437 times or 54% of all responses, which is almost twice as likely (1.79x) of responses of Enhanced (58,386 responses/30%) and 3.36x more likely than responses of Manipulated (31,004 responses/16%).

The number of correct answers, on average, was proportional to the number of images to which a participant responded. Out of all the participants that responded to all 164 images presented in the survey, the highest percentage of correct responses was 50%, with the average for all participants close to 37% correct. Figure 6 illustrates the number of participants' correct responses compared to their number of total images responses.

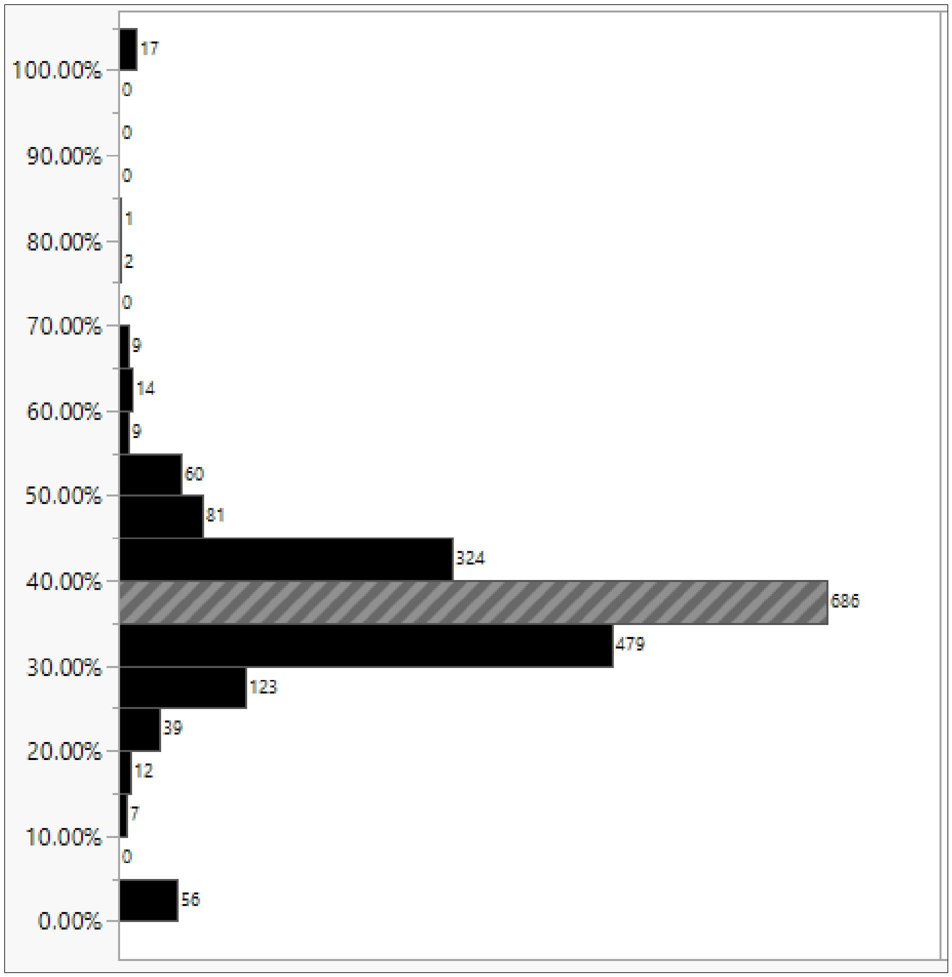


Figure 6. Distribution of participants' percent of correct responses. The highlighted column shows most participants had a 35-40% accuracy rate.

The percentages of correct responses were calculated by dividing the number of total correct responses per participant by the number of images to which they responded. Overall, there was an average correct rate of 37%. Most participants had a correct response rate of 33%, with a standard deviation of 11%. However, these statistics do not account for the difference between a participant who responded to all 164 images and the one participant who only responded to one image.

When the participants are categorized by the number of images to which they responded, the relationship of correct answers to number of responses can be determined by the equation: $y = 0.0067x + 0.3641$ with an R^2 of 0.0059. The equation found that regardless of the amount of survey completion, the average participant would only have s 36.41% correct responses, with a slight increase as the number of images to which they responded increased. Figure 7 illustrates this by plotting the number of responses against the average percent of correct responses for the percent of the survey completed.

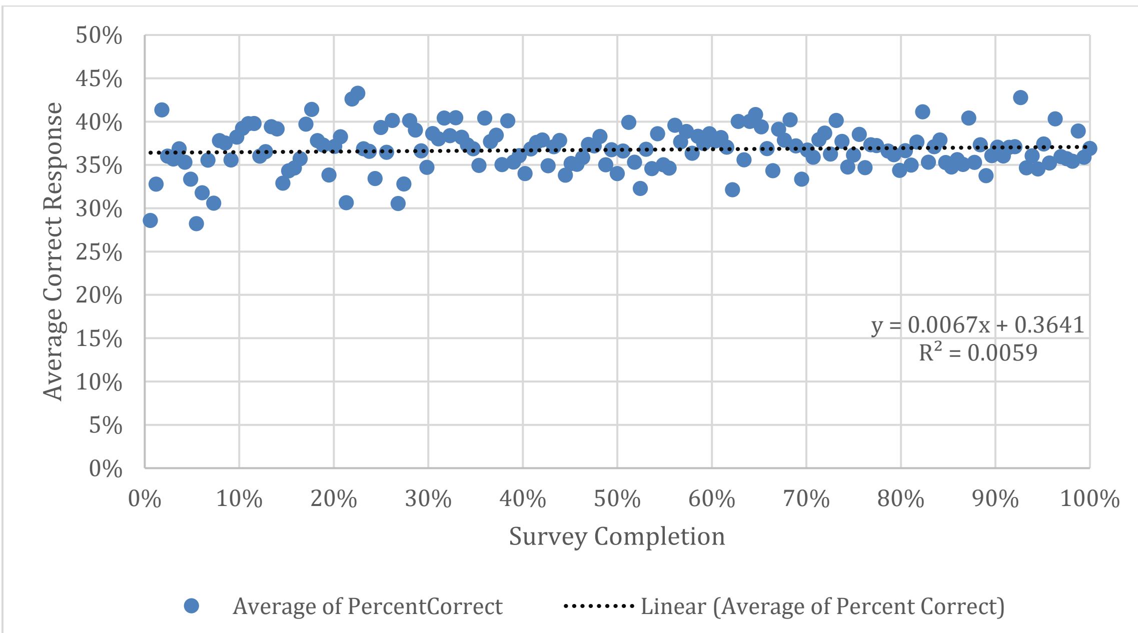


Figure 7. The average number of correct responses is not related to the number of images responded to by participants. 100% of survey completion signifies that those participants responded to all 164 images.

The average amount of time spent on each image does not show a strong relationship to the average number of correct responses. Figure 8, illustrates that the majority of responses occurred in twenty seconds or less, no matter if that participant averaged more correct responses or fewer. Figure 8 highlights that for most participants, the percent of correct responses was not strongly related to how long they took to respond to the image.

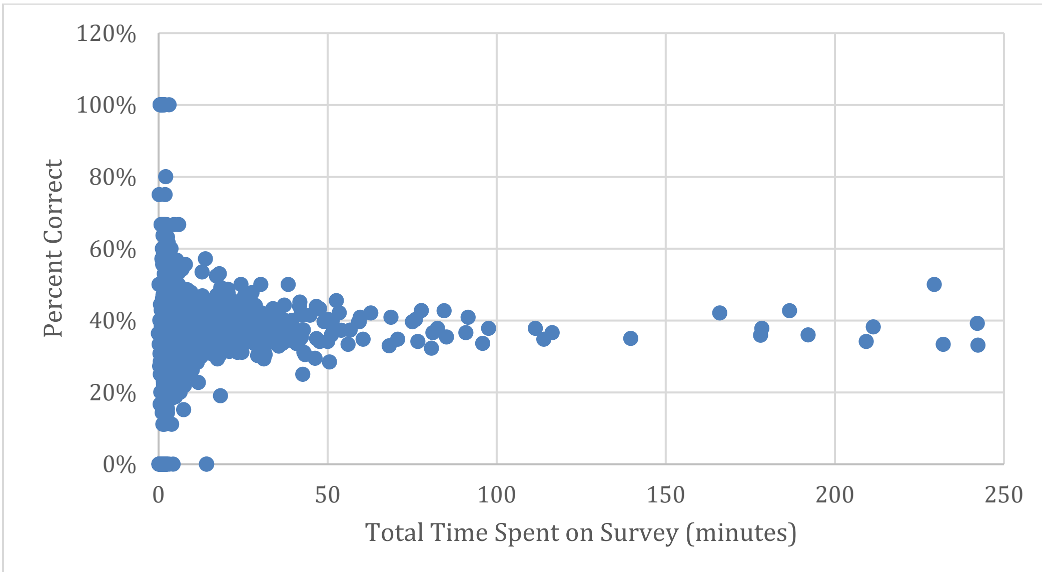


Figure 8. The average number of correct responses is plotted against the average response time per image that the participant spent per image (some outliers not depicted).

Thus, it can be deduced that in response to Research Question 1 media consumers, generally, can correctly identify an image as either manipulated, original, or enhanced in about 37% of the images that they see. It is important to note that the more images that they viewed did not change this statistic. However, this does not consider the effect that participants responded to images as *Original* more often than *Manipulated* or *Enhanced,* and some images had a much higher or much lower percent correct than the average. This is explored more in Research Question 2.

Research Question 2

The second research question asked: Does the type of image processing or the image content change the ability of the participant to distinguish between the different levels of post-processing? The percent of correct responses overall was 36%. However, this is not weighted to take account of participants who received a 100% correct score by answering and correctly responding to only one image. Alternatively, if the percent correct per image is considered, the average correct response increases to 41.6%.

In this section, the differences in response between images are explored. The images had two main categories of annotated features: manipulation and semantic category. These variables are:

Manipulation Categories

- Original
- Enhanced
- Manipulated
    - Add
    - Remove
    - Change

Semantic Categories

- People, Indoors
- People, Outdoors
- No People, Indoors
- No People Outdoors

Manipulation categories pertain to the type of post-processing that was applied to the image. The semantic category pertains to characteristics inherent to the content of the photograph. The difference in correct answers between images of different manipulation categories was significant. Based on the response, images were categorized as original twice as many times as enhanced and three times more often than manipulated images. The difference between the images based on the semantic category is discussed second.

Differences in response based on the manipulation category

There were six more images that were Manipulated than Original (53 Originals, 52 Enhanced, and 59 Manipulated Images). Participants were three times more likely to respond to an image as Original. People were most likely to categorize an image as Original. Consequently, there were more correct responses for original images. The number of responses for each image was recorded. When looking at the distribution of responses, each image was responded to an average of 1,182 times. There was a minimum of 1,173 responses and a maximum of 1,193 responses with a standard deviation of 4.25 responses.

Figure 9 illustrates that the original images were more likely to be responded to correctly as Original. There were a few images with a high number of correct responses, but the majority had fewer than 500 correct responses. Enhanced images fell between original and manipulated in the number of correct responses.

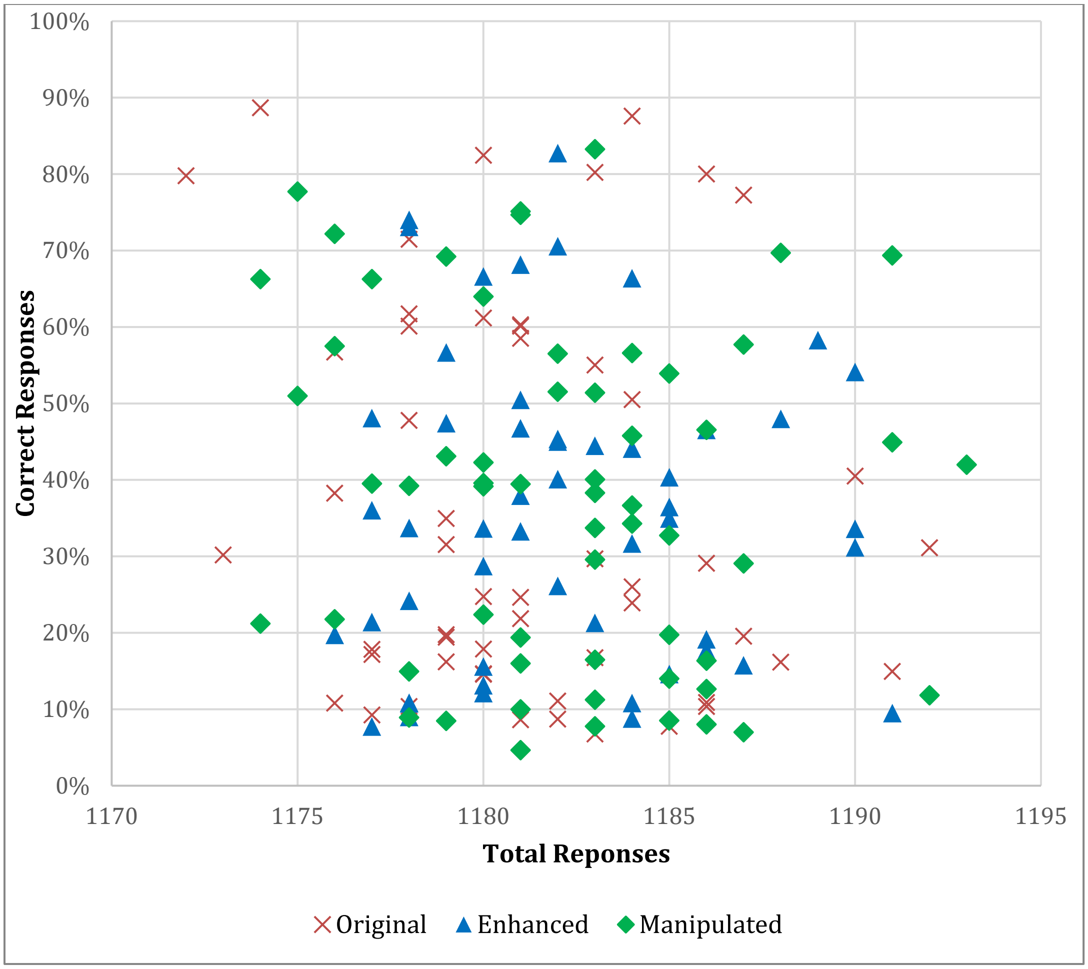


Figure 9. *Distribution of correct responses. Each point represents one image. Orange x's represent original images. Green dots represent enhanced images. Blue diamonds represent images that are manipulated. The placement of each marker represents the number of responses on the x-axis, compared to the number of those responses which correctly assigned the image on the y-axis.*

Of the 164 images, 29 images had less than a 15% correct identification rate, 28 of those were manipulated, and one was enhanced. Only 21.2% of responses correctly answered that an Original image was original. The percentage of original images with correct responses is almost double that of enhanced, and almost triple of that of manipulated images. The full distribution is listed in Table 2.

Table 2

Comparison of Correct Responses and Participant Responses

	Participant Response		
Correct Response	Enhanced	Manipulated	Original
Enhanced	12%	5%	15%
Manipulated	10%	8%	18%
Original	8%	3%	21%

In Table 2, the percentages represent the number of all responses where the participants' responses aligned with the correct response. Participants responded to images as Original with a 21% accuracy. A false-positive in this setting is defined as the participant responded that the image was one category of post-processing when it belonged to one of the other two categories. For example, a participant responded to an image as Original, when it was Manipulated. The false-positive rate for original images was 33%. Participants responded to images as Enhanced with a 12% accuracy, and there was a false-positive rate of 18%. Participants responded to manipulated images with an 8% accuracy, and the false positive rate was also 8%.

Out of ten images with the highest percentage of correct responses; nine were original images; one was manipulated. Those ten images had an 80% to 88.6% correct score. The five manipulated images with the highest percent of correct answers all had additional objects or people added. The percent correct scores ranged from 81% correct to 57% correct. The average percent correct for manipulated images is 22.72%. This average is slightly better when only considering manipulated images where something was added in, with an average percent correct of 30.11%. Images with removals had an average percent correct of 13.4%. Images with changes had an average percent correct of 21.46%.

Next, it is important to look closely at the distribution of correct answers over images that had additions (Add), removals (Remove), or significant changes (Change), There were 25 images in the Add, 17 in the Remove, and 17 in the Change category. Images with removed content were less likely to be correctly categorized as Manipulated. Images with additions were only slightly more likely to be correctly identified as Manipulated than images with significant changes. Images with significant changes (Change) had the widest distribution of correct answers without any outliers.

Knowing that the participants were more likely to answer that any image was an original, the global patterns were compared to the percentages correct in order to see if the percentage of correct responses per the assigned manipulation category was statistically different from the total percentage of responses per category. Table 3 lists the different manipulation categories, the percentage correct, and the percent of the total participant response.

Table 3

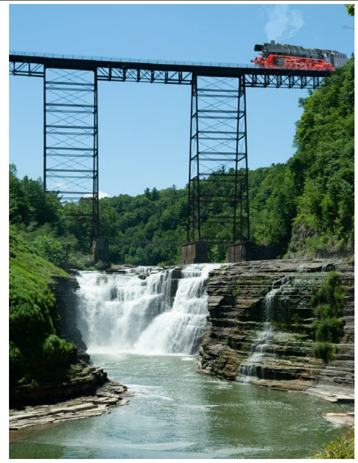
Proportion of Answers per Manipulation Category

Category	Average % Correct	% All Responses	% All Images
Enhanced	39%	30%	32%
Manipulated	23%	16%	36%
Original	66%	54%	33%

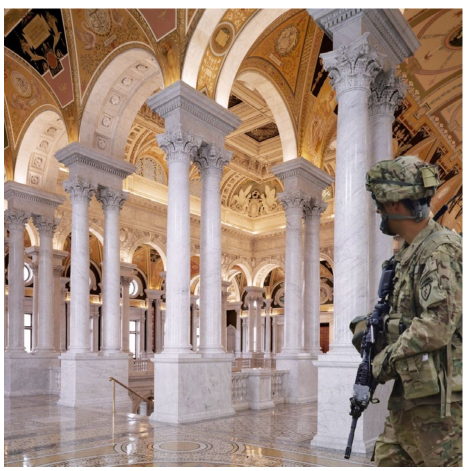
The percentage of all Original responses is almost double that of the actual proportion of original images in the dataset. The average distribution of correct answers per category is not centralized around the means of the average percent correct when organized in 5% groupings except for enhanced images. The histograms representing the distributions can be found in Appendix D.

Though participants were more likely to answer that any enhanced image, or any manipulated image, was Original, there were a couple of manipulated images that had a strong correct consensus. The images that had the highest rate of correct responses fell in the Add sub-category. The manipulated images with the highest likelihood of being responded to correctly are depicted in Figure 10.

81% correct responses: The dolphins on the left were added into the image. (Heusner, Christine. [photograph] (copyright permission of Christine Heusner))



70% Correct responses:The train in the upper right-hand corner was added into the image. (Heusner, Christine. [photograph] (copyright permission of Christine Heusner))



64% correct responses: The man in miliary fatigues was inserted into the right-hand side of the image. (Original Image: Highsmith, Carol M, .(c1980) *Great Hall, second floor, north. Library of Congress Thomas Jefferson Building, Washington, D.C* [photograph] Retreived from: http://loc.gov/pictures/resource/highsm.13970/)

58% correct responses: The man and the dog in the lower right hand corner of the image were added. Hodgson, Joyce. [photograph] (copyright permission of Joyce Hodgson)

Figure 10. Manipulated images with the highest percentage of correct responses.

The commonality among these images is that they all have a person, animal, or object added into the image. Though the placement of those subjects is not inherently absurd (dolphins in the water, train on a trestle, a man in a hallway, hiker and man on a hiking trail), their placement, size, and semantic relationship to their surroundings are large visual cues that they do not belong. The design of this study did not allow for the exact reasoning for why these images were identified as Manipulated more than half the time when compared to the rest of the images in the set.

The data do not fit the assumptions needed for a parametric analysis of variance (ANOVA). A non-parametric analysis of variance was chosen by means of Friedman's two-way analysis of variance (Altman, 1991). The data fit the assumptions of this test as it consists of three mutually independent random variables (manipulation sub-categories), and the observations may be ranked according to some criterion of interest (percent correct) (Conover, 1999, p. 177). A Friedman test was run to determine if there were differences in the percentage of correct responses between the image manipulation sub-categories of Add, Remove, and Change (Altman, 1991; Conover, 1999). A Freidman test is a non-parametric test used to detect differences across multiple test attempts. Participant responses were included in this analysis only if they had responded to at least five images in each of the sub-categories. Therefore, this analysis was completed using the answers of 1,313 participants. Pairwise comparisons were performed with a Bonferroni correction for multiple comparisons. A significance level of 0.05 was used in the following comparisons. In order to reduce the likelihood of incorrectly rejecting a null hypothesis, a Type I error, the Bonferroni correction was applied for hypothesis testing.

The Bonferroni correction uses a significance level that is divided by the number of hypotheses tested. In this case, α = 0.05/3 = 0.0166 (Chen, Feng, & Yi, 2017). The percentage correct was statistically significantly different between the three types of the images' manipulation sub-category; $X^2(2) = 689.405$, $p < 0.0005$. Post hoc analysis revealed statistically significant differences in images with content changed (*Mdn* = 0.2941) and content removed (*Mdn* = 0.1765) ($p < 0.0005$); images with content removed and content added (*Mdn* = 0.32) (p < 0 .0005) and images with content changed and images with content added (p = 0 .006). These comparisons are illustrated in Table 4.

Table 4

Percentage Correct Based on Manipulation Sub-category Image Description.

	Add (*Mdn* = 0.32)	Remove (*Mdn* = 0.1765)
Change (*Mdn* = 0.2941)	$p = 0.006$	$p < .0005$
Remove	$p < .0005$	

Another grading scheme, which creates a binary correct/incorrect scoring system that assigns the answer of either enhanced or original for *Enhanced* and *Original* images as correct, is explored briefly in Appendix B. Further exploration between the responses to images that fall in different semantic categories is explored in the next section.

Differences in response based on the semantic categorization of the image

The semantic image annotation given to images was based on whether the content of the photograph included people or not, or whether they were indoor or outdoor scenes. As noted in Figure 11, the percentage correct for each image was based on the number of responses it had. Each point represents an image. The color and shape are based on the semantic image annotations. The distribution does not suggest that there is as stark a separation in correctness based on these categories, as was found amongst the differences in the manipulation category, as seen previously in Figure 9.

Figure 11. Each image included in the experiment is placed in the figure based on the number of correct responses vs all the responses. The shape and color of the marker represent the annotation of the image-based on semantic properties.

The data do not fit the assumptions needed for a parametric analysis of variance (ANOVA). A non-parametric analysis of variance was chosen by means of Friedman's two-way analysis of variance (Altman, 1991). The data fit the assumptions of this test as it consists of three mutually independent random variables (semantic categories), and the observations may be ranked according to some criterion of interest (percent correct) (Conover, 1999, p. 177). A Friedman test was run to determine if there were differences in the percentage correct by the semantic image categories (People/No People, Indoors/Outdoors) (Altman, 1991; Conover, 1999). Participant responses were included in this analysis only if they had responded to at least five images in each of the sub-categories. Therefore, this analysis was completed using the answers of 1,373 participants. Pairwise comparisons were performed with a Bonferroni correction for multiple comparisons. A significance level of 0.05 was used in the following comparisons. In order to reduce the likelihood of incorrectly rejecting a null hypothesis, a Type I error, the Bonferroni correction was applied for hypothesis testing. The Bonferroni correction uses a significance level that is divided by the number of hypotheses tested. In this case, $\alpha = 0.05/4 = 0.0125$ (Chen et al., 2017). The percentage correct was statistically significantly different among the three semantic categories $X^2(2) = 124.612$, $p < 0.0005$. Post hoc analysis revealed statistically significant differences in the percent correct of the images with People Outdoors (*Mdn* = 0.3800) and No People Outdoors (*Mdn* = .3400) ($p < 0.0005$); No People Outdoors and No People Indoors (*Mdn* = .400) ($p < 0.0005$); People Indoors and People Outdoors (p; < 0.0005); People Indoors (*Mdn* = 0.4300) and No People Indoors ($p < 0.0005$); No People Outdoors and People

Indoors ($p = 0.014$). There was no statistically significant difference in the percent correct of the images with People Outdoors and No People Indoors ($p = 0.291$). These findings are illustrated in Table 5.

Table 5

Semantic Image Description Comparison

	No People Outdoors (*Mdn* = 0.3400)	People Indoors (*Mdn* = 0.4300)	No People Indoors (*Mdn* = 0.3400)
People Outdoors (*Mdn* = 0.3800)	$p < 0.0005$	$p < 0.0005$	$p = 0.291$
No People Outdoors		$p = 0.014$	$p < 0.0005$
People Indoors			$p < 0.0005$

The lack of a statistically significant difference between the percentage of correct responses with images with No People Indoors and People Outdoors could be because of the large difference between the number of images in each category (No People Indoors: 17, People Outdoors: 69).

Conclusion

Overall, this survey found that participants had an image dependent ability to respond correctly, thus answering Research Question 1. However, across all 164 images, an average participant score was about 37%. In regards to Research Question 2, which explored if image manipulations or the semantic category of the image lead to a change in the ability of participants to respond correctly, the data suggest that there is a statistical significance between the images that were included in this survey based on their assigned manipulation sub-categories and semantic categories.

The data show that participant response was image dependent. Some images were easier for participants to respond correctly to than others. For example, images with additive manipulations were more likely to be spotted than those with removals. However, participants overall answered that images were originals for about half of all responses. A discussion of the implications, limitations, and possible extensions to this research is discussed in the next chapter.

Chapter 7
Discussion and Conclusion

This study explored how well the general public can determine the level that images are processed. This chapter discusses further (a) how these results relate to the literature and (b) the limitations of this study. The chapter concludes with a discussion of the implications for industry and the opportunities for further research.

Results Relating to the Literature

Overall, the survey results showed that participants were more likely to respond that an image was original than manipulated or enhanced. There were statistically significant differences between images that had been manipulated with either additions, removals, or changes in content. There were also statistically significant differences in the percent of correct responses between images with or without people and images that were of indoor or outdoor scenes. However, the null hypothesis could not be rejected in the case of a comparison of the percent of correct responses for images that fell into the no people indoors and people outdoors. There was a significant difference between the number of images in those two categories that could have contributed to the lack of statistical significance.

As stated in the literature cited, photojournalistic images rely on the trust that people extend to various sources and factors, which motivates them to believe in what they see in images and miss the modifications made to the original image content through manipulation (Ball et al., 2014; Beck et al., 2007; Farid, 2006; Gavard, 1999; Gottfried et al., 2019; Mihailidis & Viotty, 2017; Newman et al., 2018; Nightingale et al., 2017;

Norris, 2017; Oriez, 2009). Media consumers view many of their images on digital platforms; therefore, it was important that this survey was conducted on the participants' devices, much like they would consume any other digital media.

This survey's results were similar to past studies concerning how the human visual system perceives images and the truthfulness of depicted subject-matter in the real-world or simulated scenes (Ehinger et al., 2016; Farid & Bravo, 2008; Mader et al., 2017; Nightingale et al., 2017; Oriez, 2009). These studies often found that participants had difficulty discerning between images that were either manipulated or original, but some images were much easier to detect. For example, people often overlooked images with slightly incorrect shadows but could identify when they were very wrong (Ehinger et al., 2016). In this research, an image was included that had a shadow of one person in a group of people standing outside skewed so that it was at a different angle than the shadows for the rest of the group. That image had 74.68% correct responses, which was much higher than the average correct score for a manipulated image (18.94%). As found in *Humans Are Easily Fooled By Digital Images,* "preference was given toward visually easy-to detect forgeries" (Schetinger, Oliveira, et al., 2017, p. 144). The manipulations that were easiest for participants to respond correctly either had people in them, were poorly scaled, or had misaligned additions. However, other manipulations included in the survey that did not align with physics or had semantic incongruities were not identified as manipulated by more than half of participants, yielding to a lower percent correct score.

A deeper, qualitative analysis of how the image subject and the image manipulations related to the ability for average consumers to discern the post-processing category was outside the scope of this study and was not readily supported by the experimental design. A further discussion of the limitations of this study is explored in the next section.

Limitations

Due to the narrow focus of this study, there are multiple limitations to the conclusions discussed. They can be divided into two main categories:

1. Limitations from survey image curation
2. Limitations on participant demographic information

Limitations from survey image curation

Designing a study to comprehensively test how accurately media consumers can look at photojournalistic images and respond if they are original, enhanced, or manipulated would require a much larger pool of images than were included in this study. Image subjects included in this survey were not necessarily easily recognizable to all participants. Though scenes were representational of photojournalistic images, not all the images included well-known figures or landmarks. The familiarity with the images or subject matter could affect the ability of participants to categorize an image correctly.

Images included in this survey were all manipulated or enhanced by the researcher. This limited the manipulations to the bounds of her creativity, ability, and time. Using images from a larger pool of manipulators could lead to different results.

Thirdly, there was not the same number of images in each semantic image category, manipulation category, or manipulation sub-category. This could lead to limitations on the ability to gain generalizations about how well people can correctly respond to the image based on these categorizations of images.

Limitations on participant demographic information

The survey mechanism was created with the priority of being simple to navigate and to record anonymous responses. Because of these design decisions, there were limitations to the amount of information that could be recorded to aid in the analysis. No demographic data was recorded about the participants, so it is difficult to discern which if any populations performed differently than others. The researcher cannot ensure that the results are representative of any general population.

This survey had many images and little participant feedback, as participants did not know how many images were left in the survey, or if they had responded correctly to the image. Most participants who reached out to the researcher through comments on social media or directly to the researcher mentioned their frustrations and growing apathy in the task. This survey design did not allow the survey data to illustrate how engaged the participants were, or how easy or hard they found the task. These limitations lend this preliminary study to be a good starting point for future research. These research opportunities are discussed in the next section.

Opportunities for Further Research

In future studies, it would be beneficial to distribute the survey to a wider population. A special focus on recruiting more international participation could lead to a more nuanced answer. Tracking demographic data could also lead to more insights into what characteristics influence people's abilities.

Using recruitment methods that are not predominantly reliant on sharing the survey through social media could be beneficial in understanding more about people's abilities to determine if the images were original, manipulated, or enhanced. Placing the invite to the survey link next to popular news media, could offer insights about whether certain audiences perform better on detecting image manipulations. For example, do people who read the newspaper (and participate in the survey from that link) have more correct responses than people who access the survey through a Facebook ad?

By including learning opportunities, financial incentives, or other gamification strategies, heightened participant engagement could alter task performance. Learning strategies could include increasingly difficult manipulations. For example, simple manipulations such as compositing a simple vector image and raster photograph could gradually build up to sophisticated GAN (Generative Adversarial Network) image face-swaps.

Other opportunities for further qualitative research based on this study could include asking a set of participants to write captions for original images and compare them to captions written for manipulated versions of those images. This could determine the magnitude of manipulation needed to change the semantic meaning of an image. This is important when determining if an alteration to an image is closer to an enhancement versus a manipulation.

Implications

This study is interdisciplinary as it relates to areas of study including psychology, photography, journalism, digital media, vision, media literacy, media forensics, and image manipulation. Consequently, this study could have both practical and theoretical implications for various industry groups relevant to those domains.

The results from this study could inform publishing companies or social media companies on how they might want to label their images if they have been altered in any way, even if it might seem obvious to the image editor. Once the images are out of context, some people can find distinguishing between images with different types of post-processing to be difficult. To protect the credibility of photojournalism, the strict guidelines from the NPPA and World Press Photo Agency should be adopted (Campbell, 2014; National Press Photographers Association, n.d.). It is especially relevant to recognize that the source of the image is a crucial clue to media consumers on the provenance and truthfulness of the depiction (Alexander, Wood, Alexander, & Wood, 2019; Roche, Pickett, & Gertz, 2016).

For news consumers, the present study could be a reminder to slow down and think more critically about the images that they see on their news aggregation platforms as previous studies show that individuals often trust what they see inherently (Newman et al., 2018; Norris, 2017). This study showed that when viewed quickly without context, participants were more likely to respond to images as original more frequently than the other options. The results of this study could prompt the viewers to not rely as heavily on the image alone but also to consider at the context in which it is published for information about its validity.

Educators could use this study as an impetus to include more tasks building visual competency skills in their classrooms. Images can be persuasive (Newton, 2001). For example, educators could reference this study to bring awareness to their students to think more critically about the images they are presented in the news. For school administrators, this study could demonstrate how the importance of media literacy and visual competency education, which can support the incorporation of these subjects into the curricula.

For forensic scientists, this study could confirm how easily the human visual system can be convinced that an image is an original when there has been a significant manipulation. This could be further impetus to fund and research computational media forensics methods that examine non-visual manipulation fingerprints. With the immense scale of the images being published, a computational triage system to sort manipulated, enhanced, and original images, is imperative for accurate intelligence gathering and situational awareness.

For journalistic photography editors, this study could be used as a reminder to ensure the strong provenance trail of any image they wish to publish as news. Also, it could stand as reason to publish any manipulation done to the image, even if it seems to them as poorly done, visually obvious, or semantically absurd. Having the ground truth published is helpful for media consumers and policy makers to have confidence that they understand what they are seeing.

The field of vision science could use this study as a starting point to explore the variables that trigger the response in participants that an image is original, enhanced, or manipulated. This study found that there is a statistically significant difference in response correctness for different types of manipulation and subject matter. This realization indicates that more studies that focus on those differences could be illuminating to human perception and help inform other disciplines further on where the gaps in ability lie.

Conclusion

This study asked participants to distinguish between images that have been manipulated (processed unethically), enhanced (processed ethically), or are unaltered as the next step in understanding how media consumers interpret the image content published by news sources. The results of this study suggest that individuals, when presented with a set of images, will say that they are original if no major manipulation is detected. However, what a *major manipulation* is to one person could be completely accepted as truth by another.

Major manipulation of the image does not always have to happen in post-processing. By changing the framing of an image, it portrays a different scene. Alexander Gardner manipulated a journalistic image by moving a body to make compelling American Civil War images (Library of Congress, n.d.). In the modern journalism community this can be seen just as deceitful just as *Time Magazine* taking a small crying child and creating a photo-illustration where she looks like she is looking up at President Trump with the headline: “Welcome to America” (Vick, 2018). Though the latter is easier to perceive as a photo-illustration rather than a deceitful photograph, neither are considered ethical photojournalism. Photojournalist Nancy L. Ford emphatically explains on her website:

> The Time Magazine cover photo illustration depicting the sobbing child looking up at President Trump is horribly exploitative of the child.
>
> Shame on Time.
>
> But just as bad is Time Magazine taking a credible news photo and cutting out the child to create the illustration. Chopping up a legit news photo to create a photo illustration is bad because it blurs the public's view of the line between reality and photoshopped images, which in turn erodes the credibility of not just photojournalism, but journalism as a whole. Society needs to trust that the photos they are looking at are the truth. If Time is going to consider themselves as a news magazine, they must not alter the truth. (Ford, 2018).

Re-framing images either in-camera or in post-processing is unethical according to the NPPA's Code of Ethics (National Press Photographers Association, n.d.) which can be seen as American photojournalist's unified standards of ethics (Bersak, 2006). The ability to capture realistic images and reproduce them efficiently propelled photojournalism to increased levels of popularity. Free image manipulation software is easy to find on the Internet. Many people have access to high quality digital cameras in their smart phones. Publishing images through social media has made it easier than ever for citizen journalism to flourish. However, there are photographers and publishers who push what a realistic interpretation of the event depicted is a reason for further discussion.

Every photograph is an edited reflection of reality: some elements are included; some are left out. The world of color can become black and white, or otherwise distorted. Lenses can give superhuman abilities and apply fun-house mirror levels of distortion. Artistic manipulation can elevate the mundane to the spectacular.

After photographer Brian Walski digitally manipulated an image to combine two images of a soldier directing civilians was published on the front page of the *Los Angeles Times* he was dismissed after the alteration was discovered (“Editor’s Note - Los Angeles Times,” 2003). However, not everyone agreed with this move. Walski’s editorial decision was supported by Meyer who argued that the essence of the photograph was not altered: “The only explanation I can find, is that by accusing the photographer and attempting to portray themselves as publishing "unmanipulated" news, they are seeking to conceal the factual reality of their biased and one-sided presentation of the overall news.” (Meyer, n.d.) While this study concludes that what constitutes a major manipulation varies widely among the respondents, it is clear that to a majority of viewers, a presumption of non-manipulation is inherent to the experience.

Image capture and manipulation, therefore, have always been at the heart of photojournalism, and today’s readily available technologies only democratizes these abilities further. While much has been written about the ethics of photojournalism and image forensics, there has been scant published research found involving the ability of individuals to recognize manipulated images in the context of the current media landscape. It is hoped that the present study illuminates this further.

The resultant data from the present study suggest that individuals, when given a set of images, will say that they are original if no major manipulation is detected. This premise underscores the responsibilities of those involved in photojournalistic workflows. The intrinsic power of images together, with the presuppositions of the viewing public, creates a paradigm where cognition of that condition needs to be at the forefront of image manipulation decisions. It is this requirement for integrity that the present study primarily accentuates.

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Appendix A

Augmenting Information: Google Analytics

A variety of participation acquisition techniques were employed, including word of mouth, social media posts, and direct emails. Figure A-1 breaks down the Google Analytics results that describe the traffic sources for the survey.

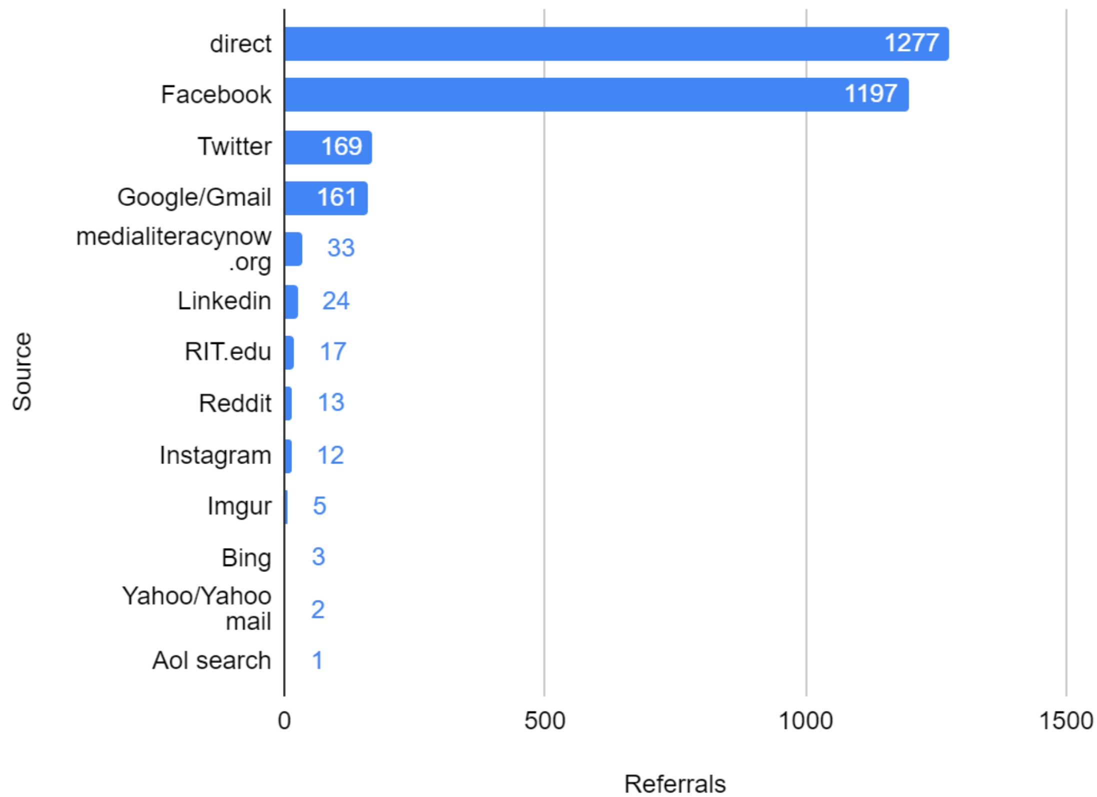

Figure A-1 Facebook was the largest online referral for participants, even eclipsing the number of direct links.

Google Analytics also revealed that many users had IP addresses that could be traced to Western New York. However, there were several countries and other regions of the United States represented. There were no demographic questions included in the survey to verify these results.

Participation Data

Time per image response was measured in milliseconds. Table A1-1 displays a review of the distribution of response time for all images and for response time per image, without outliers. Table A-1 lists common descriptive statistics for two related distributions. *All images* column refers to the response time across all the images a participant viewed. The *Per image* column refers to the response time per image, regardless of the participant responding.

Table A-1

Descriptive Statistics of Time Taken on the Survey

Descriptive statistic	All images	All images without outliers	Per image with outliers	Per image without outliers
Mean	16 minutes 48 seconds	8 minutes, 53 seconds	9.98 seconds	3.80 seconds
Standard deviation	1 hour, 23 minutes, and 35 seconds	4 minutes, 22 seconds	8 minutes, 10 seconds	1.84 seconds
25th percentile	3 minutes, 57 seconds	5 minutes, 20 seconds	1.94 seconds	2.28 seconds
Median	8 minutes, 15 seconds	8 minutes 15 seconds	3.30 seconds	3.30 seconds
75th Percentile	14 minutes, 27 seconds	11 minute, 57 seconds	6.11 seconds	4.96 seconds
Minimum	0 minutes, 0 seconds	2 minutes, 24 seconds	0.01 seconds	1.5 seconds
Maximum	1 day, 21 hours, 27 minutes, 22 seconds	19 minutes, 30 seconds	1 day, 21 hours, 14 minutes, 47.85 seconds	8.70 seconds

The Means of both distributions were skewed left because of the very large maximum times without removing the outliers. When outliers were removed, the average time per participant spent on the survey was close to 8 minutes 53 seconds, almost half of the mean without removing the outliers.

Appendix B
Alternative Response Grading

The definition of enhanced, in this study, includes changes to the image that does not intend to change the content or semantic meaning of the image. For photojournalistic purposes, this could be considered an original image. The responses were then categorized as Original (Original + Enhanced) and Manipulated. The data show that participants are more likely to respond to a Manipulated image as Original or Enhanced, but not confuse an Original (or Enhanced) image for being manipulated. The percent correct for Enhanced and Original images increases as illustrated by Figure B-1.

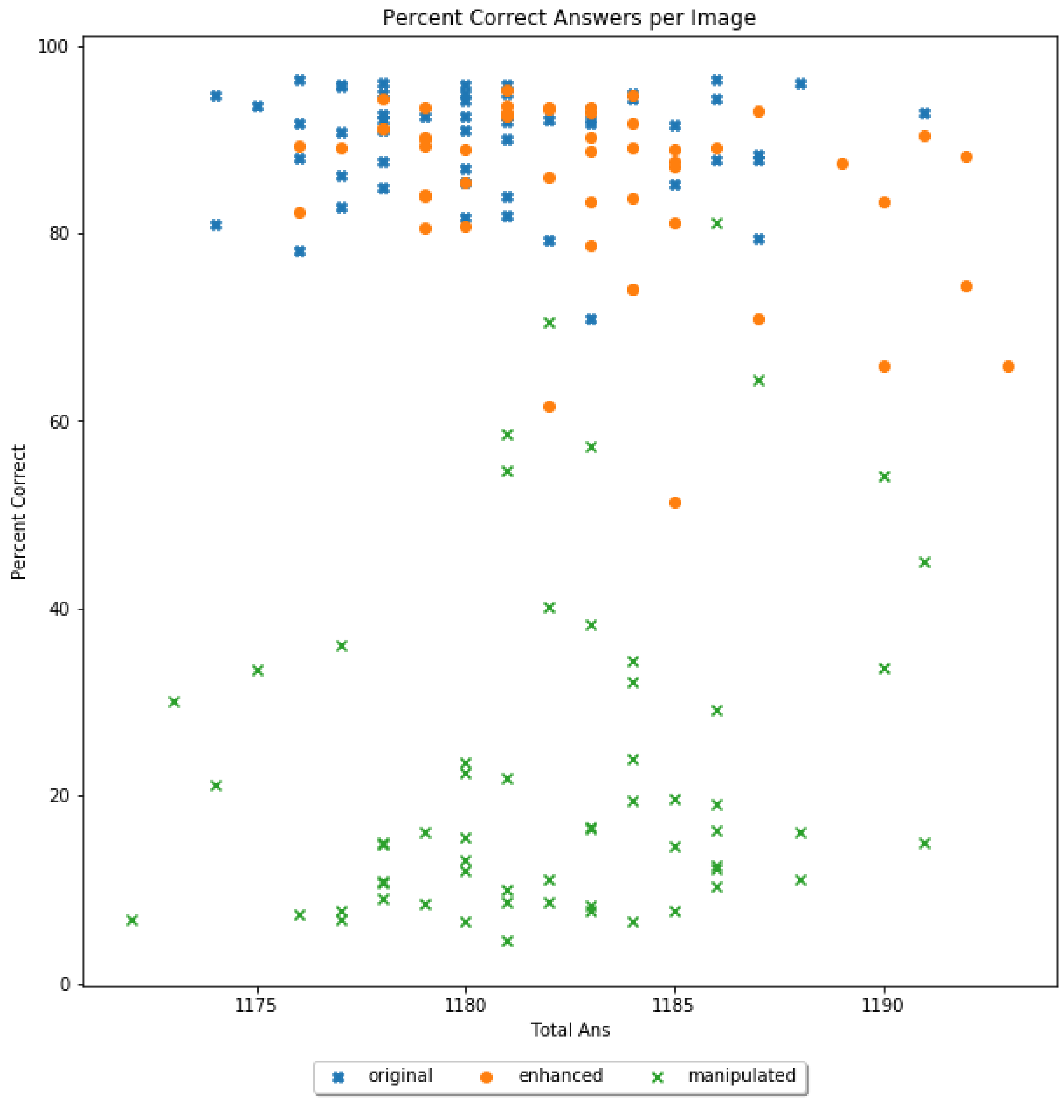

Figure B-1: Percent correct increased for all original and enhanced images when participant responses were considered correct if they responded to them as either original or enhanced.

Overall, if the participants did not automatically identify a manipulation, they were more likely to categorize the image as *Original*.

Appendix C

Image Characteristics and Response Summary

Table C-1:
Image characteristic and response summary

Image ID	Answered Enhanced	Answered Original	Answered Manipulated	Number Correct	Number of Responses	Semantic Group	Manipulation Sub-Category	Manipulation Category
10588	489	552	145	345	1187	No People Outdoors	Original	original
10589	308	534	345	122	1178	No People Outdoors	Enhanced	enhanced
10590	122	882	174	198	1183	No People Outdoors	Add	manipulated
10591	149	836	198	128	1178	No People Outdoors	Change	manipulated
10592	385	665	128	80	1183	People Outdoors	Removed	manipulated
10593	298	805	80	708	1180	No People Outdoors	Original	original
10594	324	708	146	882	1181	People Outdoors	Original	original
10595	182	882	117	172	1180	People Outdoors	Change	manipulated
10596	427	581	172	256	1176	People Indoors	Enhanced	enhanced
10597	256	822	98	826	1192	People Outdoors	Original	original
10598	280	826	85	465	1177	People Indoors	Original	original

Continuation of Table C-1:
Image characteristic and response summary

Image ID	Answered Enhanced	Answered Original	Answered Manipulated	Number Correct	Number of Responses	Semantic Group	Manipulation Sub-Category	Manipulation Category
10599	663	465	49	462	1178	No People Outdoors	Original	original
10600	612	462	104	232	1188	No People Outdoors	Enhanced	enhanced
10601	232	818	137	651	1183	People Outdoors	Original	original
10602	448	651	84	482	1191	People Outdoors	Enhanced	enhanced
10603	482	301	407	210	1186	People Outdoors	Enhanced	enhanced
10604	210	933	43	598	1185	No People Outdoors	Original	original
10605	206	598	380	141	1192	People Outdoors	Add	manipulated
10606	298	753	141	432	1186	No People Outdoors	Enhanced	enhanced
10607	432	176	577	462	1180	People Outdoors	Enhanced	enhanced
10608	462	670	48	474	1184	No People Outdoors	Original	original
10599	663	465	49	462	1178	No People Outdoors	Original	original

Continuation of Table C-1:
Image characteristic and response summary

Image ID	Answered Enhanced	Answered Original	Answered Manipulated	Number Correct	Number of Responses	Semantic Group	Manipulation Sub-Category	Manipulation Category
10609	365	474	344	532	1182	People Outdoors	Original	original
10610	573	532	77	232	1177	No People Indoors	Enhanced	enhanced
10611	232	687	257	985	1185	No People Outdoors	Original	original
10612	105	984	94	755	1180	No People Indoors	Original	original
10613	356	755	69	596	1181	People Outdoors	Original	original
10614	499	596	86	388	1186	People Outdoors	Enhanced	enhanced
10615	388	622	175	861	1179	No People Indoors	Original	original
10616	270	861	47	778	1174	People Indoors	Original	original
10617	173	778	223	563	1178	People Outdoors	Original	original
10618	512	563	103	95	1187	People Outdoors	Enhanced	enhanced
10619	95	128	963	834	1184	People Outdoors	Add	manipulated

Continuation of Table C-1:
Image characteristic and response summary

Image ID	Answered Enhanced	Answered Original	Answered Manipulated	Number Correct	Number of Responses	Semantic Group	Manipulation Sub-Category	Manipulation Category
10620	197	151	834	127	1177	No People Outdoors	Add	manipulated
10621	528	522	126	599	1176	People Indoors	Enhanced	enhanced
10622	599	183	393	55	1181	People Indoors	Change	manipulated
10623	177	949	55	252	1183	People Indoors	Removed	manipulated
10624	623	308	252	292	1180	People Outdoors	Enhanced	enhanced
10625	292	661	227	570	1188	People Indoors	Enhanced	enhanced
10626	570	486	132	258	1181	People Outdoors	Add	manipulated
10627	434	489	258	189	1181	People Outdoors	Change	manipulated
10628	94	898	189	949	1186	People Outdoors	Original	original
10629	170	949	67	499	1180	People Outdoors	Original	original
10630	402	499	279	308	1185	No People Indoors	Removed	manipulated

Continuation of Table C-1:
Image characteristic and response summary

Image ID	Answered Enhanced	Answered Original	Answered Manipulated	Number Correct	Number of Responses	Semantic Group	Manipulation Sub-Category	Manipulation Category
10631	474	402	308	448	1181	People Outdoors	Enhanced	enhanced
10632	448	519	214	786	1184	People Outdoors	Original	original
10633	168	786	230	101	1186	People Outdoors	Add	manipulated
10634	181	903	101	780	1177	No People Indoors	Original	original
10635	235	780	162	522	1184	People Outdoors	Original	original
10636	564	522	98	639	1185	People Indoors	Enhanced	enhanced
10637	639	399	147	211	1181	People Outdoors	Enhanced	enhanced
10638	211	880	89	978	1182	People Outdoors	Original	original
10639	110	978	94	913	1175	No People Outdoors	Original	original
10640	186	913	76	786	1181	People Outdoors	Original	original
10641	287	786	107	350	1183	People Indoors	Original	original

Continuation of Table C-1:
Image characteristic and response summary

Image ID	Answered Enhanced	Answered Original	Answered Manipulated	Number Correct	Number of Responses	Semantic Group	Manipulation Sub-Category	Manipulation Category
10642	155	350	678	173	1180	People Outdoors	Add	manipulated
10643	444	563	173	252	1177	People Outdoors	Original	original
10644	798	252	127	210	1177	No People Outdoors	Enhanced	enhanced
10645	210	886	81	109	1178	People Outdoors	Removed	manipulated
10646	175	893	109	949	1183	People Outdoors	Original	original
10647	136	949	98	536	1182	People Outdoors	Original	original
10648	191	536	455	414	1185	People Outdoors	Enhanced	enhanced
10649	414	618	153	608	1185	People Outdoors	Enhanced	enhanced
10650	608	476	99	128	1184	No People Outdoors	Add	manipulated
10651	460	596	128	467	1180	People Outdoors	Enhanced	enhanced
10652	467	583	130	667	1177	No People Outdoors	Enhanced	enhanced

Continuation of Table C-1:
Image characteristic and response summary

Image ID	Answered Enhanced	Answered Original	Answered Manipulated	Number Correct	Number of Responses	Semantic Group	Manipulation Sub-Category	Manipulation Category
10653	667	423	86	133	1183	No People Outdoors	Add	manipulated
10654	691	359	133	104	1184	People Outdoors	Enhanced	enhanced
10655	104	1014	66	935	1173	People Indoors	Original	original
10656	158	934	80	192	1188	People Outdoors	Removed	manipulated
10657	290	706	192	129	1186	People Outdoors	Add	manipulated
10658	569	488	129	397	1181	People Outdoors	Enhanced	enhanced
10659	397	705	78	92	1184	No People Indoors	Change	manipulated
10660	274	817	92	105	1178	No People Outdoors	Removed	manipulated
10661	296	777	105	670	1185	People Outdoors	Original	original
10662	435	670	79	202	1177	No People Indoors	Change	manipulated
10663	524	451	202	291	1181	No People Outdoors	Original	original

Continuation of Table C-1:
Image characteristic and response summary

Image ID	Answered Enhanced	Answered Original	Answered Manipulated	Number Correct	Number of Responses	Semantic Group	Manipulation Sub-Category	Manipulation Category
10664	245	291	645	155	1181	People Outdoors	Change	manipulated
10665	424	601	155	83	1187	No People Indoors	Removed	manipulated
10666	597	507	83	187	1189	No People Outdoors	Enhanced	enhanced
10667	187	235	765	113	1191	People Indoors	Add	manipulated
10668	307	771	113	118	1181	People Indoors	Enhanced	enhanced
10669	118	1002	61	869	1181	People Outdoors	Original	original
10671	93	979	106	106	1179	No People Outdoors	Change	manipulated
10672	87	1037	60	1037	1184	People Indoors	Original	original
10673	375	501	308	375	1184	People Outdoors	Enhanced	enhanced
10674	391	727	60	727	1178	No People Outdoors	Original	original
10664	245	291	645	155	1181	People Outdoors	Change	manipulated

Continuation of Table C-1:
Image characteristic and response summary

Image ID	Answered Enhanced	Answered Original	Answered Manipulated	Number Correct	Number of Responses	Semantic Group	Manipulation Sub-Category	Manipulation Category
10675	371	620	199	371	1190	People Outdoors	Enhanced	enhanced
10676	233	717	229	233	1179	People Indoors	Enhanced	enhanced
10677	396	505	283	283	1184	People Indoors	Add	manipulated
10678	412	653	114	412	1179	People Outdoors	Enhanced	enhanced
10679	380	712	89	712	1182	No People Outdoors	Original	original
10680	309	793	80	309	1182	People Outdoors	Enhanced	enhanced
10681	668	385	126	668	1180	People Outdoors	Enhanced	enhanced
10682	415	581	184	184	1180	People Indoors	Add	manipulated
10683	526	461	196	526	1184	No People Outdoors	Enhanced	enhanced
10684	450	518	208	450	1176	People Indoors	Enhanced	enhanced
10685	243	842	93	842	1178	No People Outdoors	Original	original

Continuation of Table C-1:
Image characteristic and response summary

Image ID	Answered Enhanced	Answered Original	Answered Manipulated	Number Correct	Number of Responses	Semantic Group	Manipulation Sub-Category	Manipulation Category
10686	127	916	144	917	1189	People Outdoors	Original	original
10687	80	466	644	644	1190	No People Outdoors	Add	manipulated
10688	148	864	173	173	1185	People Outdoors	Change	manipulated
10689	323	679	176	176	1179	No People Outdoors	Removed	manipulated
10690	281	798	100	100	1179	No People Outdoors	Add	manipulated
10691	242	809	131	131	1182	People Outdoors	Removed	manipulated
10692	339	451	400	400	1190	No People Outdoors	Change	manipulated
10693	316	437	424	424	1178	People Indoors	Change	manipulated
10694	484	595	103	103	1183	People Indoors	Change	manipulated
10695	577	509	91	91	1177	People Indoors	Removed	manipulated
10696	458	676	42	676	1176	No People Indoors	Original	original

Continuation of Table C-1:
Image characteristic and response summary

Image ID	Answered Enhanced	Answered Original	Answered Manipulated	Number Correct	Number of Responses	Semantic Group	Manipulati on Sub-Category	Manipulation Category
10697	229	763	187	229	1180	People Outdoors	Enhanced	enhanced
10698	327	805	49	805	1181	No People Outdoors	Original	original
10699	552	553	76	552	1181	People Indoors	Enhanced	enhanced
10700	546	467	178	178	1193	No People Outdoors	Add	manipulated
10701	609	407	166	609	1183	No People Indoors	Enhanced	enhanced
10702	511	414	249	249	1175	No People Indoors	Add	manipulated
10703	359	600	227	227	1186	No People Outdoors	Add	manipulated
10704	241	722	217	722	1180	People Outdoors	Original	original
10705	393	703	85	393	1181	No People Indoors	Enhanced	enhanced
10706	559	430	190	559	1180	People Indoors	Enhanced	enhanced
10707	430	663	92	92	1185	People Outdoors	Removed	manipulated

Continuation of Table C-1:
Image characteristic and response summary

Image ID	Answered Enhanced	Answered Original	Answered Manipulated	Number Correct	Number of Responses	Semantic Group	Manipulation Sub-Category	Manipulation Category
10708	259	685	243	685	1188	No People Outdoors	Original	original
10709	693	346	150	693	1192	People Indoors	Enhanced	enhanced
10710	137	899	150	150	1186	People Outdoors	Removed	manipulated
10711	219	872	87	872	1179	People Outdoors	Original	original
10712	686	339	155	339	1180	People Outdoors	Original	original
10713	276	712	191	191	1179	People Outdoors	Removed	manipulated
10714	283	709	194	194	1186	People Outdoors	Removed	manipulated
10715	501	284	408	501	1193	No People Outdoors	Enhanced	enhanced
10716	371	517	304	371	1192	People Outdoors	Enhanced	enhanced
10717	242	466	474	474	1182	No People Outdoors	Add	manipulated
10718	187	849	140	849	1176	People Outdoors	Original	original

Continuation of Table C-1:
Image characteristic and response summary

Image ID	Answered Enhanced	Answered Original	Answered Manipulated	Number Correct	Number of Responses	Semantic Group	Manipulation Sub-Category	Manipulation Category
10719	460	591	127	127	1178	No People Outdoors	Change	manipulated
10720	466	660	55	466	1182	No People Outdoors	Enhanced	enhanced
10721	327	492	354	354	1173	People Outdoors	Removed	manipulated
10722	314	828	46	828	1189	No People Outdoors	Original	original
10723	71	1041	62	1041	1174	No People Outdoors	Original	original
10724	447	331	406	406	1184	No People Outdoors	Change	manipulated
10725	240	250	691	691	1182	People Outdoors	Add	manipulated
10726	434	558	192	434	1184	No People Indoors	Enhanced	enhanced
10727	166	795	224	166	1185	No People Outdoors	Enhanced	enhanced
10728	372	691	116	372	1179	People Indoors	Enhanced	enhanced
10729	256	660	264	264	1181	People Indoors	Add	manipulated

Continuation of Table C-1:
Image characteristic and response summary

Image ID	Answered Enhanced	Answered Original	Answered Manipulated	Number Correct	Number of Responses	Semantic Group	Manipulation Sub-Category	Manipulation Category
10730	542	580	62	542	1184	No People Outdoors	Enhanced	enhanced
10731	269	668	245	668	1182	People Outdoors	Original	original
10732	275	816	88	816	1179	People Outdoors	Original	original
10733	399	669	115	399	1183	People Outdoors	Enhanced	enhanced
10734	177	887	117	887	1182	No People Indoors	Original	original
10735	327	661	195	195	1183	No People Indoors	Add	manipulated
10736	603	397	178	397	1181	No People Indoors	Original	original
10737	285	827	66	285	1178	People Outdoors	Enhanced	enhanced
10738	191	846	143	143	1180	No People Outdoors	Change	manipulated
10739	550	401	234	234	1185	No People Indoors	Add	manipulated
10740	478	576	131	478	1186	People Indoors	Enhanced	enhanced

Continuation of Table C-1:
Image characteristic and response summary

Image ID	Answered Enhanced	Answered Original	Answered Manipulated	Number Correct	Number of Responses	Semantic Group	Manipulation Sub-Category	Manipulation Category
10741	590	140	453	453	1184	People Indoors	Change	manipulated
10742	376	710	95	710	1181	No People Outdoors	Original	original
10743	427	414	345	345	1188	People Outdoors	Removed	manipulated
10744	351	755	77	351	1183	People Outdoors	Enhanced	enhanced
10745	147	973	60	973	1180	People Indoors	Original	original
10746	384	679	123	123	1186	No People Outdoors	Add	manipulated
10747	508	593	78	508	1179	People Indoors	Enhanced	enhanced
10748	229	863	89	229	1181	No People Outdoors	Enhanced	enhanced
10749	423	656	102	102	1181	No People Outdoors	Removed	manipulated
10750	559	566	52	566	1179	No People Outdoors	Original	original
10751	414	242	535	535	1191	People Outdoors	Add	manipulated

Appendix D
Distributions of Percent Correct for Images based on Manipulation Category

This appendix includes the number of images that fall in different ranges with percent correct. The percent correct is calculated by counting all the correct participant responses and dividing that number by the total number of responses for that image. The image set included 164 images. 53 Originals, 52 Enhanced, and 59 Manipulated Images.

The first histogram (Figure A4-1) illustrates the distribution of Percent Correct for Original images.

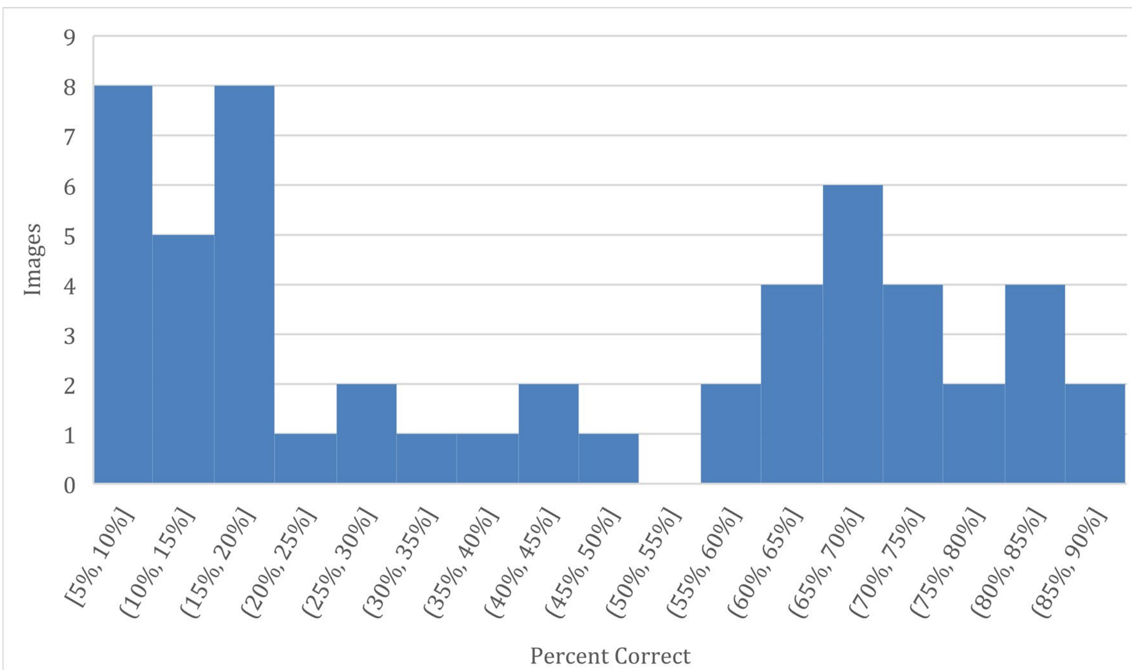

Figure A4-1: There are 53 total Original images. Images had percent correct responses ranging from 5% correct to 90% correct responses.

The second histogram (Figure A4-2) illustrates the distribution of Percent Correct for Enhanced images.

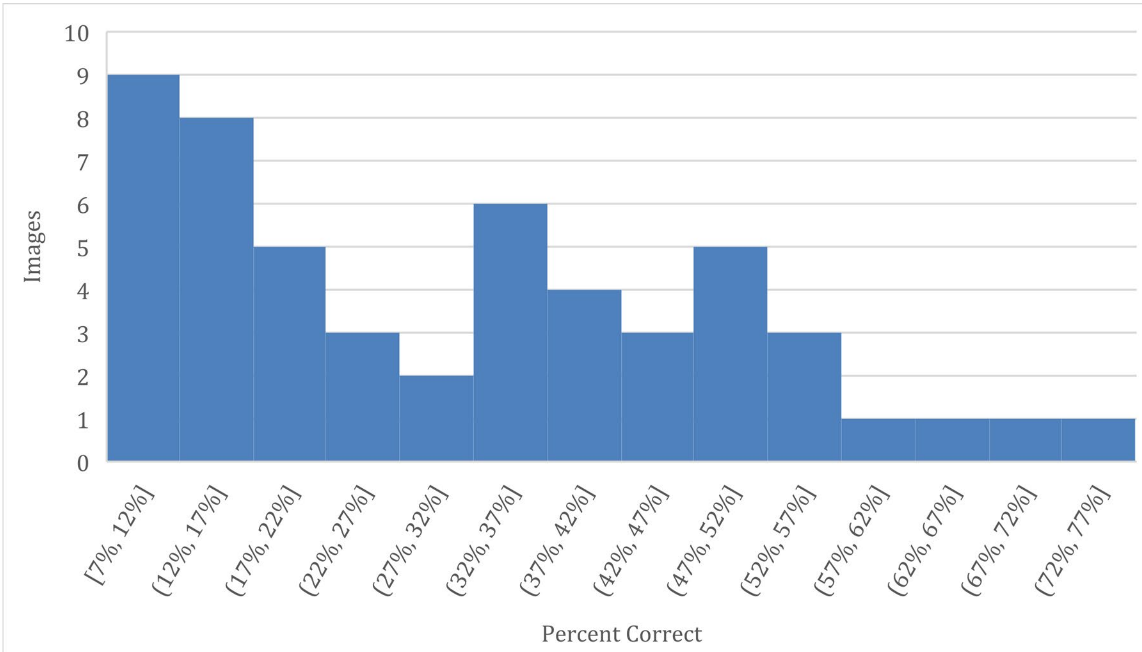

Figure A4-2: There are 52 Enhanced images. Images had a percent correct ranging between 7% and 77%.

The third histogram (Figure A4-3) illustrates the distribution of Percent Correct for Manipulated images.

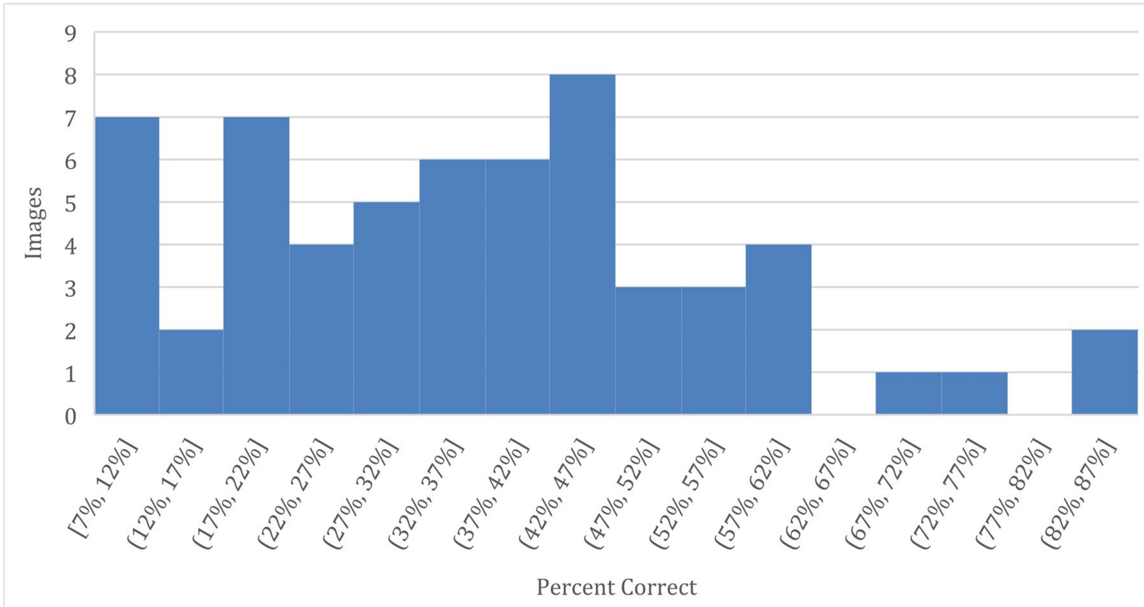

Figure A4-2: There are 59 Manipulated images. Images had a percent correct ranging between 7% and 87%.